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Review

Big Data-Driven Implementation in International Construction Supply Chain Management: Framework Development, Future Directions, and Barriers

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Abstract

Background: In any country, supply chain management is crucial to the economy. Big data-driven (BDD) implementation can be used in different disciplines, especially in construction supply chain management (CSCM). While BDD has a lot of opportunities for optimizing workflows, reducing costs, and improving collaboration among stakeholders to enhance efficiency and decision-making, its adoption is fraught with significant barriers. Thus, identifying these challenges is an important research concern. Methods: This study adopts a systematic review methodology aligned with PRISMA guidelines, combining bibliometric and thematic analyses to explore the integration of BDD approaches in CSCM. A comprehensive search of the Scopus database was conducted, focusing on articles published between 2014 and 2024 with a multi-phase screening process until 62 relevant studies were adopted. Results: This study summarizes the challenges associated with integrating BDD into CSCM and presents solutions to solve them and a framework for implementing BDD in CSCM. Moreover, providing future directions that require further consideration and research. Conclusions: By overcoming these barriers, the construction supply chain will be able to adopt big data for improving efficiency and reshaping CSCM. This study provides a clear view of how CSCM scholars and practitioners should develop along with promising research on BDD.

Keywords: construction logistics; big data-driven (BDD); supply chain management (SCM); supply chain analytics; supply chain resilience

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1. Introduction

Supply chain management (SCM) is important in the economy of every country. For example, the China logistics market was valued at around USD 2464.05 billion in 2023 and it is expected a growth rate of 6.3% from 2024 to 2032 at a compound annual growth rate [1]. The demands for employability skills in the business world of the twenty-first century are more varied and complex than they were in the past. The world's commercial environment has become more global due to advancements in information and communication technologies. Over the past few decades, people have been exposed to an infinite amount of various data due to the rapid advancements in technology and the growing usage of digital tools and the Internet [2]. The total amount of data generated, recorded, duplicated, and consumed worldwide is projected to increase quickly, hitting 149 zettabytes in 2024 and expected to surpass 394 zettabytes by 2028, according to Statista. Both human- and

machine-generated data come from a wide range of sources. Along with the amount of information, computer systems are producing information at a high rate. Companies have to use the resources and expertise of their suppliers and customers due to rapid changes, globalization of business, and unpredictability of the environment. Better internal and external information integration results from this, improving customer satisfaction and operational efficiency. Therefore, many organizations have no doubt that data science insights aid in achieving specified results.

In the same context, big data (BD) has considerable potential to improve engineering, construction, and architecture [3]. Additionally, it is becoming widely accepted in SCM to assist managers in providing competitive advantage, enhanced business performance, and sustainable value [4]. However, big data-driven (BDD) refers to the vast quantity of easily accessible data from several sources, in multiple formats, and at a rapid rate. This data is typically too big to handle with traditional data analysis tools or technologies (i.e., methods that are mostly based on relational databases and centralized computing technologies and are typically relevant to structured data with limited sample sizes) [5,6]. Furthermore, Big Data Analytics (BDA) techniques have been crucial in today's shift to Industry 4.0, which integrates sensors, the Internet of Things (IoT), and intelligent data analysis to revolutionize industrial outputs [7], also digital twin due to the capabilities of real-time monitoring and evaluation of large-scale complex systems [8]. BDA is the process of gathering data and using computer algorithms, analytical tools, and methodologies to extract patterns and meaningful and significant insights from huge amounts of data [9].

To accurately predict their demand, companies should constantly evaluate their data on both current and potential customers. Additionally, the availability of high-quality easily available data and the qualitative and quantitative analysis of that data can help businesses with their supply chain problems [10]. Enhancing supply chain operations is crucial for maintaining a competitive edge and positively affecting the company's overall performance [11]. In this regard, BDD can be used as a useful tool to increase supply chain analysis capabilities, resulting in enhanced decision-making across the supply chain [12]. Companies can use BDD techniques to convert the huge amounts of data produced through the supply chain process into meaningful insight, which makes BDD an emerging area on which numerous studies have been published in recent years. Therefore, supply chains benefit from BDD by using it to make well-informed decisions, manage risks, enhance operational processes, and carry out market research for specific items [13,14].

It is crucial for investigation into BDD challenges in the construction supply chain in the technologically advanced world of today. A proper investigation of barriers to BDD can facilitate construction companies to build more effective strategies. From conventional CSCM to BDD CSCM, many challenges will arise such as technological, organizational, human resource, economic, regulatory, and cultural barriers. Few studies have been performed to determine and examine the obstacles and difficulties in implementing BDD in China's construction supply chain. Therefore, this study helps construction supply chain practitioners analyze key barriers and find solutions to successful BDD implementation. So, in this study, five main challenges will be encountered from conventional CSCM to BDD CSCM.

(1) Data-related barriers

Data security and privacy concerns are critical, as sensitive information must be kept safe from breaches, especially in construction supply chain management (CSCM) with multiple stakeholders (e.g., contractors, subcontractors, suppliers, and owners). Moreover, performance and scalability issues arise when managing and processing vast datasets efficiently. In addition, poor data quality, including inaccuracies, incompleteness, and inconsistencies, may limit the reliability of insights. On the other hand, data integration

from various systems and stakeholders is a challenge, as well as making the data available with timely and instant access along the supply chain to support decision-making. Lastly, reliance on manual data collection with only a low percentage of processes digitized means very limited automation and advanced analytics.

(2) Technology-related barriers

One major obstacle facing practitioners in the construction supply chain and hindering the great scalability and efficiency of data-driven systems is the lack of infrastructure to store and/or transfer large volumes of supply chain data. Also, the unavailability of specific BDD tools constrains the conducting of advanced analytics and decision-making. The weak support for adoption and implementation on the part of senior managers affects organizational readiness toward the digitization of business activities, making it more difficult. Lastly, BD solutions are not able to be effectively tested and validated due to a lack of laboratories or testing facilities in companies when it comes to assessing services and data products.

(3) Organizational and human resource barriers

Lack of clear plans and strategies toward organizational goals prevents progress. Non-availability of any policy regarding sharing data between various organizations causes fragmented companies to impede collaborative works, integrations with data, and underutilized resources. Awareness or trust of insight from data itself is seriously impeded as related to organizations showing weakness in decisions based on such data. In addition, the lack of training facilities coupled with a shortage of skilled information technology (IT) personnel further makes them ill-equipped to handle and analyze the data, hence slowing down the adoption process. In addition to the weak managerial support, many organizations fail to cultivate a culture that embraces BDD decision-making.

(4) Regulatory barriers

The weakness in governance policies that support BDD development limits the development of effective frameworks. The time-consuming process of obtaining permits to implement new technologies delays innovation and adoption, legal consulting companies and a lack of expertise in BDD hinder organizations from understanding how to work within the regulatory environment. In addition, ambiguous classification of public data makes access rights difficult to determine. On the other side, incomplete legislation about right-to-use policies and weak legislation on privacy, data security, and intellectual property creates insecurity and risks among organizations.

(5) Economic and business barriers

The high cost of investing in technologies, infrastructure, and qualified employees can be a significant barrier, particularly for companies with limited funds. In addition, most senior managers in public and private organizations have a lack of sufficient knowledge regarding the economic benefits of adopting BDD technologies. Furthermore, weak alignment of business models with data-driven principles limits the integration of BD into organizational operations.

A few papers have been published to address these issues. To the best of our knowledge, no comprehensive research has been performed to compile and highlight present progress in tackling these five issues. Therefore, the purpose of this study is to examine the BDD supply chain management studies to contribute by summarizing the difficulties and obstacles in incorporating BDD technologies into the CSCM and offering solutions. Additionally, this study highlights the research gaps and suggests future directions of inquiry. In this regard, this study represents the following novel contributions to the field of BDD-CSCM:

- Comprehensive identification and classification of barriers through 62 rigorously screened studies from 2014 to 2024 using PRISMA 2020.
- An implementation framework tailored to construction projects, offering a practical roadmap for embedding BDA across project-based supply chain segments.
- A new barrier taxonomy of 21 specific obstacles grouped into five dimensions (data, technology, organizational and human, regulatory, economic) as well as targeted mitigation strategies for each.
- A forward-looking research agenda highlighting gaps in data governance, scalable infrastructure, real-time performance systems, skill development, and supportive policy frameworks, thereby steering future BD-CSCM investigations.

The structure of this study is as follows: The research methods are shown in Section 2. The key findings are presented in five categories of barriers in Section 3, and the supply chain management applications of BDD are shown in Section 4. Research gaps and future directions are discussed in Section 5, and concluding findings are provided in Section 6.

2. Research Methods

2.1. Review Methodology

The research follows the guidelines of the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) to promote transparency, accuracy, and thoroughness in reporting. PRISMA approach assists systematic and organized research using bibliometric analysis to produce strong evidence-based findings. Following PRISMA guidelines enables the researchers to systematically relate each research question to the existing knowledge in CSCM. The approach also enables the determination of thematic issues and research gaps, which can be lost in single studies, hence informing an unequivocal research opportunity agenda [15].

The research approach shown in Figure 1 is a systematic multi-phased process including stages of identification, screening, analysis, and discussion. The process of identification started by launching an extensive Scopus core database search with four specific keywords—"big data," "data-driven," "supply chain," and "logistics"—and produced 7423 preliminary records. On application of the filter for publication time (2014–2024), only 6221 papers were left. A dataset of 2923 was formed on filtering in terms of journal articles being in the language of English. These documents were utilized for yearly distribution analysis and thematic evolution timeline map to display the evolution and changing interest of research on BDD in the field of supply chains. The screening process undertaken included three complementary filtering steps: (1) the selection of 331 papers with an explicit occurrence of "construction" in the same line of their title, abstract, and keywords; (2) filtering to 117 journal publications in only journals with excluding of conference publications; and (3) application of specific contents through full-text and abstract screening, which gave 62 final papers. These shortlisted studies were subjected to bibliometric analysis in terms of country and journal contribution and keyword co-occurrence. From all these analyses, a framework for implementing BDD in CSCM is presented and five major barriers are determined. Then, the main application fields of the BDD in CSCM were discussed. Finally, limitations and future research directions are stated.

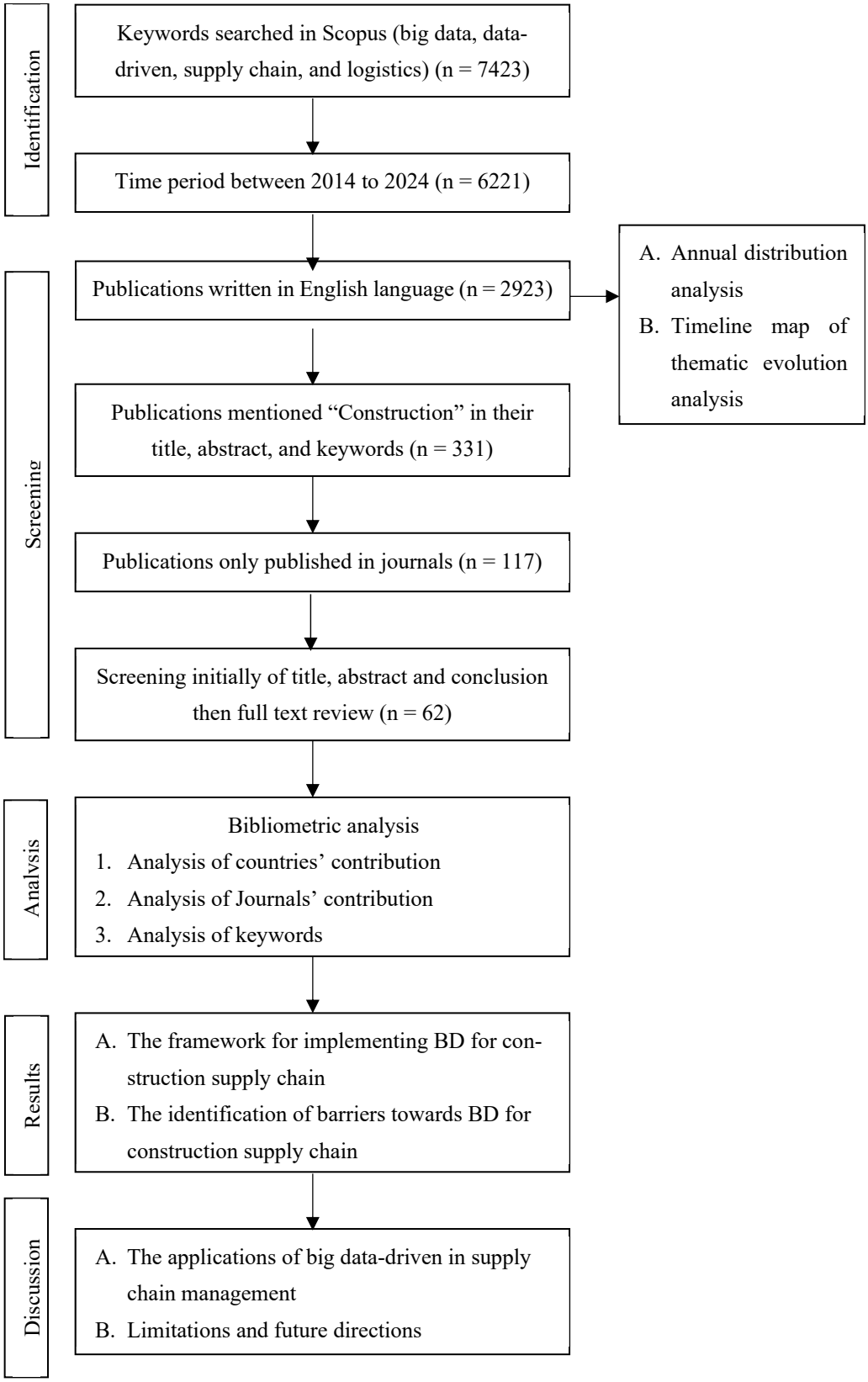


Figure 1. Flow chart of research methodology.

2.2. Trends and Thematic Evolution in Big Data-Driven Supply Chain Research

To carry on the analysis, first, the trend of annual publications over the last decade is represented, with research output reflecting growing interest then, thematic trends indicate shifting toward digital transformation, advanced analytics, and the integration

of environmentally friendly practices in pursuit of sustainable and crisis-resilient supply chains; afterwards, proceeds with the review methodology and bibliometric analysis, showing exponential growth in research on BDD supply chains; and, finally, constructs the framework of BDD for the construction supply chain.

In the past decade, several research domains have made extensive use of the BD concept, especially supply chain management. For the 2923 documents in the period from 2014 to 2024, the annual distribution is represented as shown in Figure 2. The research output has been growing from 44 publications in 2014 to 120 in 2017, then further doubling to 266 in 2020. The growth accelerates beyond 2021, with a jump from 349 in that year to 616 publications for 2024, representing an almost 77% increase over three years. This rising graph shows how BD can address modern challenges faced in supply chains like decision-making in real-time, predictive analytics, and more efficiency in the data-driven approach for better logistics and operational resilience of organizations.

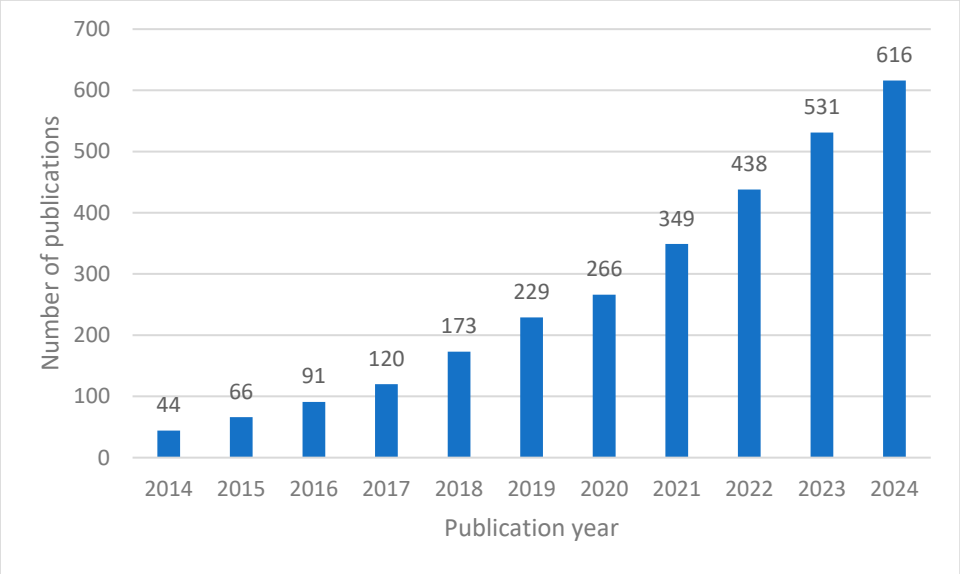


Figure 2. The number of publications related to the use of big data-driven supply chains yearly.

Additionally, CiteSpace version 6.3.R1 software was used to create a timeline map of thematic evolution that showed how BD research themes in the supply chain context developed over time. As shown in Figure 3, a keyword is represented by a node. On the top side of Figure 2, there are four years represented. Initially, the years were from 2014 to 2024. Early research (2014–2016) was focused on BD as well as SCM and decision-making, which were the core of the newly realized potential to optimize supply chains. By 2020, the focus shifted to advanced technologies such as machine learning, artificial intelligence, and blockchain, alongside topics like supply chain resilience and risk management. These emerging themes of sustainable development, the circular economy, and COVID-19 underline the emergent requirement for green supply chains, which will be capable of resilience during crises. In recent trends, for instance, there has been a focus on digital transformation toward green supply chains with the use of advanced analytics during 2022–2024. Such an evolution demonstrates how BD enables much more informed decisions, innovation, and resilience in global supply chain systems.

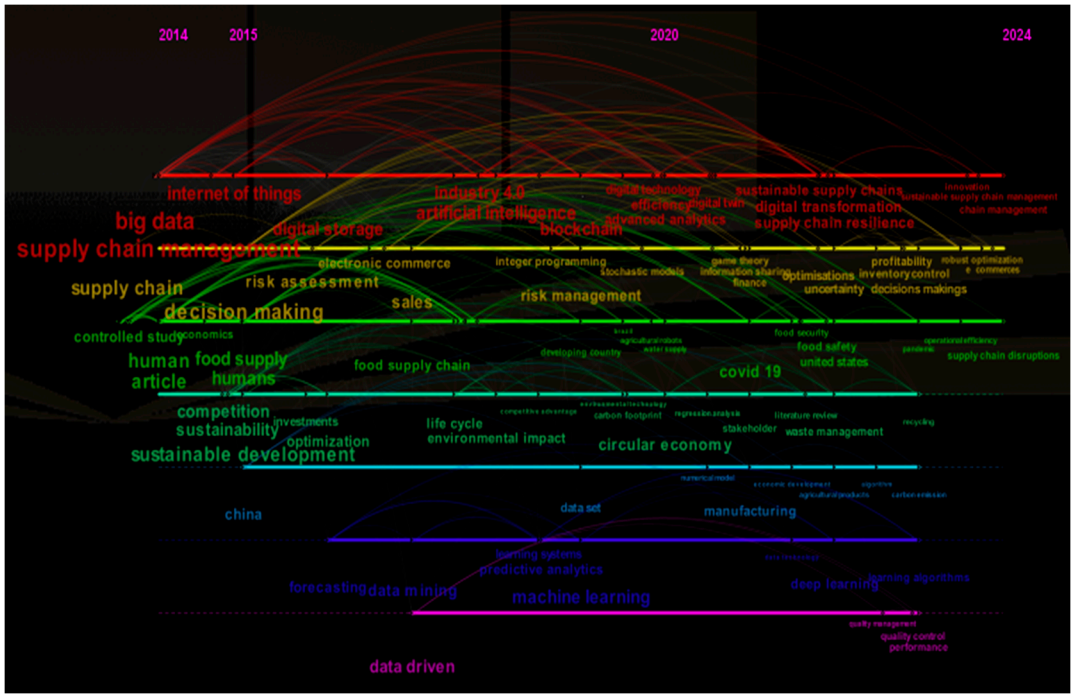


Figure 3. Documents related to BD in supply chain management timeline map.

2.3. A Review Database Bibliometric Analysis

For an immense quantity of scientific data, a bibliographic analysis identifies important patterns and insights across numerous research disciplines. This approach shows publication dynamics and collaboration patterns in addition to tracking the development of certain themes. In addition to studying the body of previously published literature on a given topic, researchers employ bibliometric analysis to identify new trends in research components, collaboration patterns, and article and journal performance [16–19]. In bibliometric analysis, a large amount of data usually takes the front stage. In other words, by thoroughly interpreting huge quantities of unstructured data, bibliometric analysis helps to map and analyze the body of scientific knowledge and complexities of evolution in established domains. Consequently, a bibliometric analysis of 62 reviewed articles is carried out to give a thorough explanation of BDD in relation to CSCM to country, journals, journal co-citation, and keyword Co-occurrence.

2.3.1. Analysis of Countries' Contribution

Figure 4 demonstrates the connections between countries and publications using a co-authorship network created with VOSviewer version 1.6.17 and a minimum of two articles published. Nodes represent countries and their relative contributions, and links show co-authorship or collaboration strength. From the network map, the global collaboration on the application of BD in construction supply chains can be seen, with interactions among major countries included. The major nodes of China, the United Kingdom, Australia, and the United States represent areas of significant contribution or leadership. Dense links, like those between the United States and China, indicate effective partnerships in BD technology development. On the other hand, smart city initiatives or integrated supply chain systems may appear in relation to regional cooperation, like between China and Hong Kong. A worldwide effort to use BD in CSCM is highlighted by links with different nations like Indonesia and Iran, which indicate opportunities for knowledge-sharing initiatives in the digitalization of the construction supply chain.

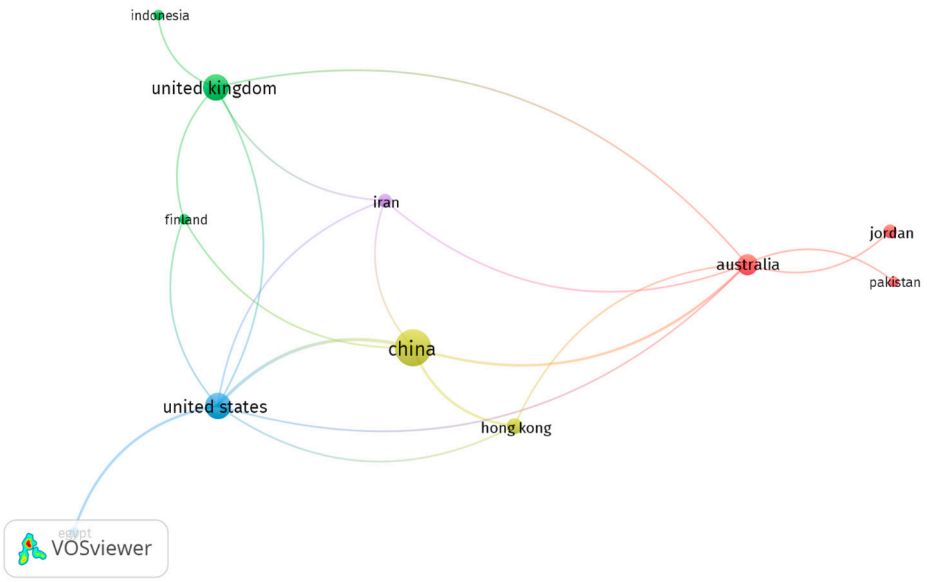


Figure 4. Global research collaboration network on BD in supply chain management.

2.3.2. Analysis of Journals' Contribution

These publications are published in more than 45 different journals. Figure 5 illustrates the distribution of publications related to BD in SCM in journals that contributed more than 2 publications. The top three journals—the *Journal of Construction Engineering and Management*, the *Journal of Cleaner Production*, and *Automation in Construction*—have the highest number of publications with four documents, which primarily focused on construction and engineering disciplines, with a distinct emphasis on technological advancements and sustainability.

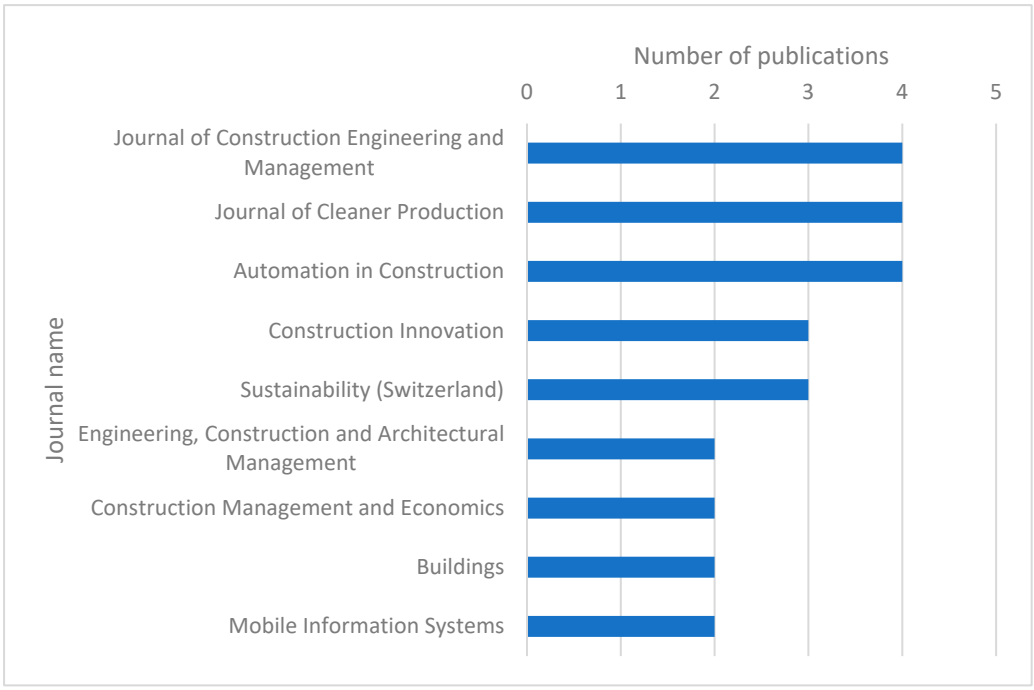


Figure 5. Distribution of publications by contributing journals on BD in CSCM.

By using VOSviewer version 1.6.17 software with a minimum number of citations of 10 per journal, a journal co-citation network was generated as shown in Figure 6, showing how journals connect to these 62 publications. Larger nodes, such as *Automation in*

Construction, the *Journal of Cleaner Production*, and *Sustainability*, indicate that these journals have high co-citation counts, reflecting their central influence in this research area and showing strong relationships with other journals through shared citations.

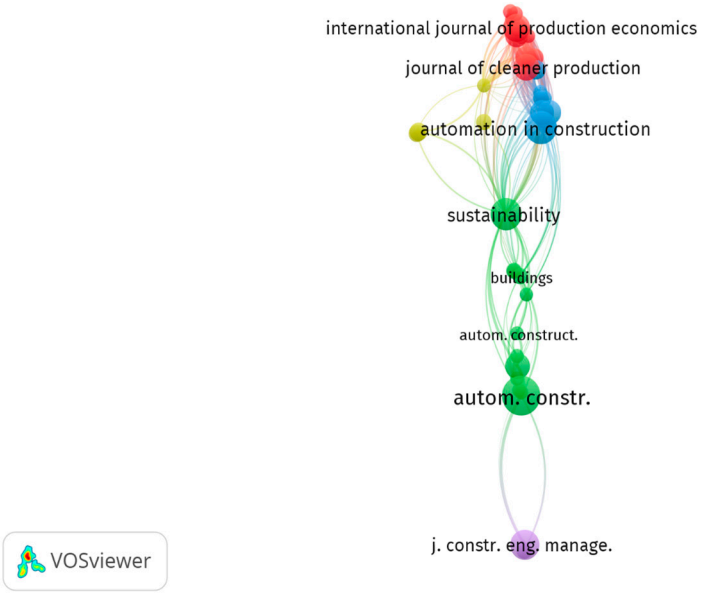


Figure 6. Journal co-citation network of the selected publications on BD in CSCM.

The top ten papers with citations in Scopus are shown in Table 1. The most cited paper, with the title "Construction with digital twin information systems", authored by Sacks et al. [20], received 340 citations and used automated data collection from supply chains and construction sites, lean project production systems, artificial intelligence, and building information modeling principles to establish a method of construction that produces closed-loop control systems using digital twin information systems.

Table 1. Highly cited papers on BD in supply chain management.

Ref.	Authors	Journal	Year	Citations
[20]	Rafael Sacks, Ioannis Brilakis, Ergo Pikas, Haiyan Sally Xie, and Mark Girolami	*Data-Centric Engineering*	2020	340
[21]	Junhu Ruan, Yuxuan Wang, Felix Tung Sun Chan, Xiangpei Hu, Minjuan Zhao, Fangwei Zhu, Baofeng Shi, Yan Shi, and Fan Lin	*IEEE Communications Magazine*	2019	163
[22]	Jannik Giesekam, John R. Barrett, and Peter Taylor	*Building Research and Information*	2016	159
[23]	Xiao Li, Weisheng Lu, Fan Xue, Liupengfei Wu, Rui Zhao, Jinfeng Lou, and Jinying Xu	*Journal of Construction Engineering and Management*	2022	142
[24]	Zhijia You and Chen Wu	*Advanced Engineering Informatics*	2019	77
[25]	Zhaojing Wang, Hao Hu, and Wei Zhou	*Computer-Aided Civil and Infrastructure Engineering*	2017	71
[26]	Zehua Xiang and Minli Xu	*Journal of Cleaner Production*	2019	70
[27]	Qian Chen, Bryan T. Adey, Carl Haas, and Daniel M. Hall	*Construction Innovation*	2020	69
[28]	Hisham Said	*Journal of Construction Engineering and Management*	2015	53
[29]	Vian Ahmed, Algan Tezel, Zeeshan Aziz, and Magda Sibley	*Facilities*	2020	51

2.3.3. Analysis of Keywords

In any field, the co-occurrence of keywords is one of the most significant factors that determines how research grows. In this regard, the keywords of the retrieved documents were considered with 5 occurrences of a keyword as a minimum. As shown in Figure 7, there are three clusters distinguished by color. The first cluster is red in color and includes but is not limited to "supply chains," "supply chain management," and the "construction industry". However, the green cluster that focuses on the "internet of things," "building information modeling," and "blockchain" reflects the integration of advanced digital tools to enable BDD decision-making and transparency. Finally, the blue cluster that includes keywords like "decision making," and "construction" showcases the critical role of analytics in improving efficiency and achieving better project outcomes. The connections between these clusters illustrate how BD technologies integrate SCM with advanced tools and systems, fostering innovation and driving advancements in construction management.

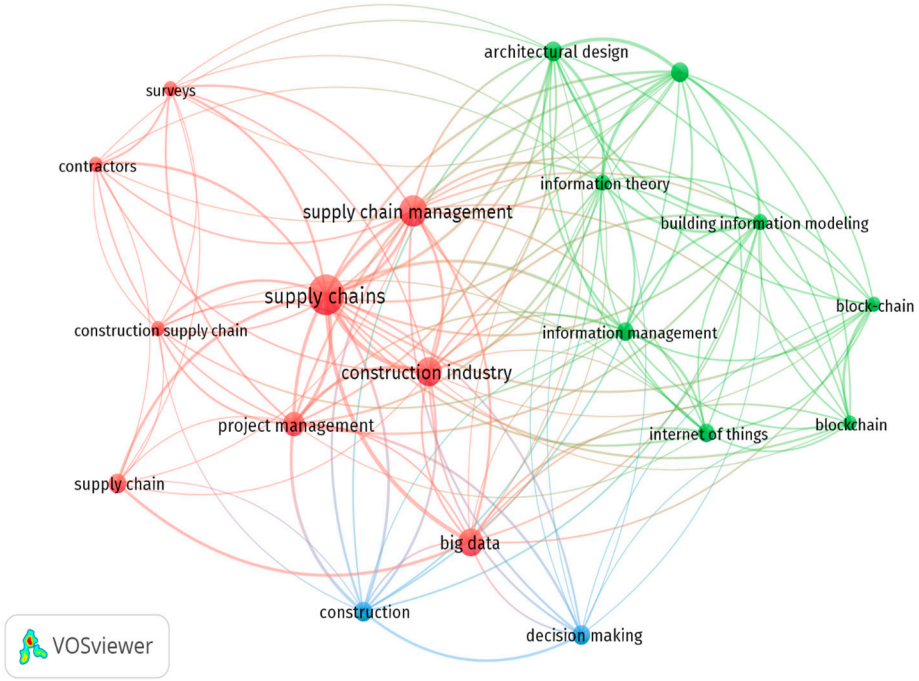


Figure 7. Keyword co-occurrence network of the selected publications on BD in CSCM.

3. Results

3.1. The Framework for Implementing BD for Construction Supply Chain

The process of applying BD to CSCM involves multiple steps. For instance, Jahin et al. [30] presented a framework that forecasts effects on the inventory, human workforce, and supply chain as a whole by integrating BDA into SCM through three crucial stages: pre-process, control process, and post-process. Margaritis et al. [31] developed a conceptual framework that uses an input–process–output model with four performance macro-areas safety, efficiency, sustainability, and quality to demonstrate the function of BD in a data-driven food SCM context. Brinch [32] offered a comprehensive framework for SCM driven by BD that is dependent on three key dimensions: value capture, value creation, and value discovery. Sanders [33] created a prescriptive framework to give organizations a roadmap for implementing BDA in four steps: first, use analytics to identify the best supply chain segments with distinct characteristics; second, align organizational activities to support segment characteristics and competitive priorities; third, measure performance and segment characteristics; and fourth, regularly refine and realign as part of the cycle.

In this study, we follow the method of Sanders [33] to construct the framework of BD in supply chain management. The primary stages shown in Figure 8 are described below. The framework segment's first stage relates to precisely defining how to compete in each segment and assists in establishing the appropriate priority and dividing the construction supply chain into distinct project-based or material-type segments according to important characteristics such as project size, urgency, material kinds, and location in order to concentrate resources and customize strategies to satisfy the various demands of various construction projects. Divide based on size, complexity, or material requirements (e.g., concrete for roads versus steel for skyscrapers) by using analytics. Establish competitive priorities for each segment. For example, just-in-time delivery for high-priority projects or cost management for large orders are examples of competitive priorities which is an essential step in segment creation. As a result, each segment has a different supply chain structure, suppliers, operational and transportation strategies, and performance standards. For instance, note that supply chain segments that compete based on quality or innovation have quite different supplier criteria than those that concentrate on cost. Utilize analytics algorithms to tailor supplier selection and inventory strategies to project specifications and schedules. This will help decision-making processes support competitive priorities in each segment, such as streamlining the construction supply chain to guarantee on-time delivery and quality within financial limitations.

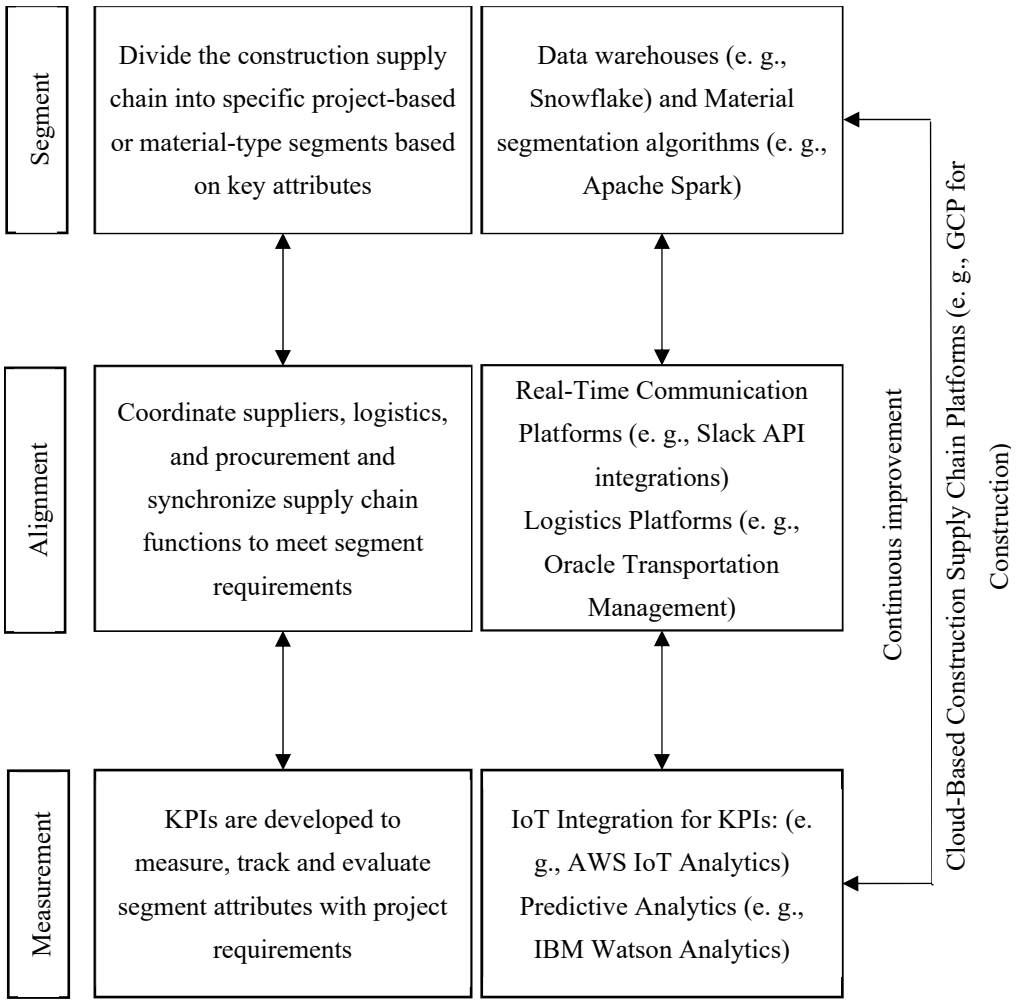


Figure 8. The framework of implementing big data-driven in CSCM.

The following stage is to align organizational functions to support segment attributes and competitive priorities. This involves synchronizing supply chain functions to facilitate joint decision-making, sharing intelligence, and integrating supply chain processes across functions and supply chain partners, as well as inventory management, procurement, and logistics to guarantee that all aspects of the supply chain, from procurement to on-site delivery, are smoothly synchronized with the objective and timeline of projects. Incorporating inventory management and demand forecasting techniques to match material supply with construction schedules by using analytics to track supply and demand in real time is one aspect of alignment. Because it facilitates "demand sensing" and influences other supply chain decisions, BD can be an important assistant in this process. To facilitate collaborative decision-making, such as optimizing delivery for phased construction projects and sharing data with subcontractors and suppliers. By concentrating on tools and systems that support segment-specific objectives, including minimizing delays or cost overruns, it may prevent fragmented analytics initiatives. Therefore, no amount of data mining will produce a system-wide competitive advantage in the absence of alignment.

In the next stage, key performance indices (KPIs) are set to measure, monitor, and assess segmental characteristics with project requirements metrics including waste reduction, material cost variation, on-time delivery rates, and project timeline adherence should be defined to ensure that supply chain decisions are driving improvements in cost efficiency, material quality, project delivery, etc. Then, these metrics should be tracked in real-time using analytics to provide early warnings of possible supply chain disruptions. Finally, feedback loops and data-driven insights are employed in continuous improvement to continuously optimize and refine the supply chain, adjust to shifting project requirements, reduce risks, and gradually increase supply chain efficiency. For instance, examine metrics to find bottlenecks, such as regular rebar supply delays, and put corrective actions in place, such as new supplier contracts, and also use analytics tools to improve logistics strategies, inventory management, and demand predictions.

3.2. Barriers Towards BD for Construction Supply Chain

Five major categories and twenty-one sub-barriers were identified from an in-depth investigation into barriers, as shown in Table 2 [14,15,34–40]. In the following subsections, a related review of the main studies that focused on and tried to solve these barriers.

3.2.1. Data-Related Barriers

When it comes to leveraging BD in the construction supply chain, data-related challenges can be broken down into several key areas, each addressing unique difficulties. Below is a detailed explanation of some of the most common obstacles.

Data security and Privacy: Ensuring data security and privacy is a significant challenge in utilizing BD within the construction supply chain. As organizations increasingly rely on interconnected systems and shared data, they become more vulnerable to potential risks and security issues [39]. Since construction companies frequently manage high-value projects involving sensitive data and significant financial transactions, they become attractive targets for cybercriminals. Bechtsis et al. [40] stated that in order to establish strategies, security has been the focus of supply chain stakeholders mostly during the planning phase.

Table 2. List of barriers based on literature review.

Barriers Category	Barriers
Data barriers	1. Data security and privacy; 2. Performance and scalability; 3. Complexity of data integration; 4. Data collection and sharing; 5. Data quality;
Technology barriers	6. Lack of infrastructural for storing and transferring big data; 7. Lack of availability of specific BDD tools; 8. Lack of performance measurements for evaluating BDD in companies;
Organizational and human barriers	9. Lack of planning to develop strategies towards using big data-driven; 10. Time constraints; 11. No policy to share data among organizations; 12. Weakness of data-driven decision-making in organizations; 13. Lack of training facilities; 14. Lack of skilled personnel; 15. Weak support of managers in implementing new technologies;
Regulatory barriers	16. Weakness of governance policies in support of BD development; 17. Weakness of government policies for new Technology Adoption; 18. Weak laws in the areas of privacy, data security and intellectual property;
Economic barriers	19. High cost of investment; 20. Lack of sufficient knowledge about the economic benefits of big data-driven; 21. Weak compliance of business models with the subject of data-driven.

According to certain research, blockchain applications can be used to store and retrieve SC data streams; it is also evident from the body of existing research that blockchain technology and cybersecurity are directly related. By using blockchain technology in a multi-echelon sustainable supply chain, Manupatia et al. [41] concentrated on the cybersecurity component. Manufacturing, distribution, and inventory control decisions were considered while importing data records into a blockchain application. Aghamohammadzadeh and Fatahi [42] proposed a blockchain technology platform and cloud service to manage corporate operations and the geographical distribution of service providers, allowing a number of providers to be assigned to client needs. Ding et al. [39] discussed how to improve the administration of the construction supply chain, especially for precast construction, by integrating blockchain technology with the Interplanetary File System (IPFS). In order to solve weaknesses such as unauthorized access and inefficiencies in current centralized solutions, this hybrid system focusses on guaranteeing data scalability, efficiency, and privacy. Then, smart contracts that incorporate encryption techniques are created to automate supply chain operations pertaining to confidentiality. Pan et al. [43] developed a framework that integrates blockchain and deep learning technologies through decentralized data storage, preserving data authenticity, and preventing data manipulation to improve the efficacy of equipment supervision, decision-making, and accident tracking in equipment security management.

Performance and Scalability: Performance challenges arise when BD systems fall short in delivering the necessary speed, reliability, or efficiency, potentially hindering real-time analytics and decision-making, which are vital for effective supply chain operations [44]. Fernando et al. [45] examined how the performance of the services supply chain is affected by service supply chain innovation capabilities, data security, and BDA and found that the ability of a company to handle data security is positively and significantly correlated with the BDA, which also has a favorable effect on the performance and innovation capacities of

the service supply chain. Kamble and Gunasekaran [46] found and compiled 25 measures for BDA capability and 130 measures for BDD supply chain operations. Additionally, it was noted that new performance metrics based on the growing application of social and predictive analytics in the BDD supply chain have emerged. Gunasekaran et al. [47] showed that integrating BD predictive analytics improves supply chain performance by increasing cost effectiveness, visibility, and resilience. It also improves organizational performance by facilitating more strategic decision-making and improving market response.

Storing large-sized files is another name for the data scalability problem [39]. When a BD system is unable to manage an increase in workload or dataset size, scalability problems occur. Scalability is essential in the construction supply chain since supplier chains frequently grow and complexity as projects do. Organizations may face more cost difficulties if they use cloud computing capabilities to store BD because BD generation will increase. Over time, the cost of using cloud storage will also rise. To combat this, companies can implement strategies to streamline the data collection process and cut down on unnecessary data generation at the source [48]. Xiao et al. [49] created a cyber–physical system based on blockchain technology to enhance construction site management. IPFS is used for sharing huge files in massive volumes due to the high expenses of processing power and the high latency for file exchange.

Complexity of Data Integration: The process of retrieving and combining data from multiple sources to create information that is both understandable and practical is known as data integration [50]. One of the major obstacles to utilizing BD is the complexity of data integration. The information varies widely in structure and type as a result of the way it is collected through different sources and IoT devices [51], especially within construction supply chains, since the construction industry involves a great number of stakeholders who operate with different systems and formats, and this leads to fragmentations in data. Therefore, this stimulates the need for integration, which can be defined as a set of techniques applied to combining data from disparate sources into meaningful and valuable information. In this context, Yousif et al. [50] presented the data integration parameters and their meanings such as velocity, variety, and volume. Marzouk and Enaba [52] aimed at integrating various data types in the building information modeling (BIM) environment. After that, descriptive data analytics were performed to help improve project communication performance. This included organizing project data in a structured manner, effectively extracting relevant information from project raw data, and visualizing analytics results in the BIM environment. Vieira et al. [53] attempted to evaluate the degree of data integration used by these solutions by confirming the technologies and concepts being employed, such as manual integration, other sophisticated structures like data warehouses, or even BD concepts and technologies.

Data Collection and Sharing: The fragmented nature of the construction industry, with multiple stakeholders using disparate systems, results in inconsistent data formats and complicated sharing of data. Borkowski [54] highlighted that when integrating BIM with IoT, it is important to make sure that sensors and active/dynamic BIM models have a robust telemetric connection. In this regard, Li et al. [23] created a Hyperledger Fabric-powered blockchain-enabled IoT-BIM platform to create a trustworthy single source of truth for data about construction progress. At various project stages (such as when on-site assembly is complete), a radio-frequency identification (RFID) tag attached to the module unit is read, initiating a blockchain transaction to update the module status. By changing the state of the relevant module in the BIM file, an integrated DApp on the blockchain immediately notifies all stakeholders of this progress. You and Wu [24] presented the enterprise integrated data platform (EIDP), a BD infrastructure for construction companies, and provided a roadmap for upcoming business advancements to optimize business processes and support

decision-making to help with closed-loop CSCM, cost management and control, knowledge discovery, and decision-making to increase the effectiveness of business operations and project delivery.

To solve common problems like a lack of real-time information in precast supply chains and poor traceability and fragmentation, Wang et al. [55] proposed a blockchain information management framework for precast supply chains that would improve real-time information sharing, traceability, and scheduling management. Lee et al. [56] aimed to address the problems of inadequate information sharing, schedule synchronization, and delays brought on by disjointed workflows by utilizing blockchain technology and sensors to improve information sharing and decision-making in the volumetric construction supply chain. Elghaish et al. [57] created a framework that suggests using blockchain technology in integrated project delivery (IPD) for the engineering, construction, and architectural sectors. This will allow all parties to monitor and manage financial transactions, preventing any unauthorized alterations. The IPD core team members benefit from increased trust and transparency thanks to the automated financial system, which gives them the guarantee that all approved transactions are final and allows them to view the total amounts of profit, cost savings, and reimbursed expenses.

Data Quality: Part of the BD concern is data quality, which is a crucial factor in determining how reliable data is for decision-making. According to some tests, most sensing systems can only record one-third of the data accurately due to inaccurate readings [58]. In this regard, Abdullah et al. [59] found seven characteristics of high-quality data. The structure and content of data are often covered by the first five attributes: validity, completeness, consistency, integrity, and accuracy. Usefulness and usability are covered by the final two qualities listed above: timeliness and accessibility. Hazen et al. [60] proposed statistical process control to monitor and control supply chain data quality to advocate for the importance of addressing the quality of data in research on supply chain and practice. He et al. [61] conceptualized a framework for data quality assessing and controlling (DQAC), based on the cycle of total data quality management and designed the architecture of DQAC. This framework integrates strategies to improve data quality and proposes tools for measuring and controlling data quality in analytical applications that aim to enhance the accuracy, consistency, completeness, and usability of data.

3.2.2. Technology-Related Barriers

When BDD is integrated into supply chain management, it holds immense potential but faces several challenges in fully harnessing these technologies. These include insufficient infrastructure for storing and transferring large datasets, the absence of specialized tools tailored to the unique requirements of construction supply chains, and the lack of robust performance measurement systems to evaluate BDD processes. Below, these challenges are discussed along with some existing solutions and proposed improvements from recent studies.

Lack of infrastructure for Storing and Transferring Big Data: The lack of infrastructure for storing and transferring large volumes of supply chain data arises from legacy systems that are often incapable of handling the sheer volume and variety of BD. Additionally, limited network bandwidth leads to delays in real-time data transfer, while the high costs associated with upgrading to scalable cloud or on-premises solutions further compound the issue. These obstacles result in delayed decision-making, reduced accuracy in predictive analytics, and missed opportunities for optimization within the supply chain [33]. Chen et al. [62] provided a cloud-based system framework that uses Bigtable and MapReduce as the paradigms for data processing and storage in order to provide a web-based service for storing, viewing, and analyzing large BIMs. Web 3D and cloud technologies were used

to create a BIM data center that can manage large amounts of data from immense BIMs using a distributed system of servers and that allows numerous users to submit and view BIMs online in 3D at the same time. Cai et al. [58] analyzed cloud computing's IoT data storage technologies comprehensively and claimed that the use of data storage systems for IoT devices can boost overall data processing effectiveness and give IoT applications a significant competitive edge. Dong et al. [63] to increase the efficiency of small file storage and access on the Hadoop distributed file system (HDFS), an optimized method has been developed. While file grouping and prefetching schemes are used to manage conceptually linked small files, file merging and prefetching schemes are applied to structurally related small files.

Lack of Availability of Specific BDD Tools: The unavailability of specific BDA tools tailored to the construction supply chain poses a significant challenge. This is primarily due to the nature of construction projects, which involve a wide array of stakeholders, fragmented data sources, and highly variable workflows. Hijazi et al. [64] presented a blockchain-based BIM single source of truth data model to guarantee dependable data delivery in the construction supply chain. Through the creation of structured and trustworthy datasets, this integration encourages BIM towards digital engineering, moving from project-centric records to a digital ecosystem of linked databases by leveraging blockchain's potential to ensure trusted data. Azeroual and Renaud [65] presented the benefits of Hadoop as one of the popular BDD technologies. Hadoop is a system that satisfies BD's demands and was created as a software framework for processing tremendous quantities of data; it also developed the MapReduce framework in Hadoop. Salloum et al. [66] presented an overview of Apache Spark's primary features for BDA. With an optimized engine that supports advanced execution DAGs and APIs in, R. Spark'sMLlib, Scala, Python, and Java, Apache Spark is a general-purpose cluster computing system. Li et al. [67] claimed that the IoT sensors on construction sites are capable of performing computing jobs for data engineering and analytics in addition to implementing data collecting. AI generates findings from the useful data generated by distributed sensors. Essentially, the edges with powerful computing power bring AI closer to application scenarios and end users.

Lack of Performance Measurements for Evaluating BDD in Companies: Performance measurement is the process of evaluating an action's effectiveness and efficiency. A performance measure is a collection of metrics used to estimate the effectiveness and efficiency of an action [68]. Since the BDD supply chain performance is dynamic, fast-changing, and expected to be highly proactive, anticipating future performance rather than responding to issues after they arise, the traditional performance measurement system (PMS), which focuses on determining what happened in the past and the reasons behind it, may not be applicable [69]. Kamble and Gunasekaran [46] showed how performance metrics for BDD supply chains differ from those for traditional supply chains in that the latter must be tracked and managed in real time, requiring the performance managers to take immediate action, as well as identifying and compiling 130 measures for BDD supply chain operations. Therefore, organizations should have an integrated PMS to achieve predictive BDD supply chain performance.

3.2.3. Organizational and Human Resource Barriers

The organizational and human resource-related obstacles to BD adoption in the construction supply chain are considerable. These difficulties, which ultimately lead to dispersed efforts and underutilization of resources, include but are not limited to poor strategic planning, time constraints, and the lack of any data-sharing strategy. The appropriate use of BDA technology is further hindered by a lack of managerial support, inadequate training facilities, a lack of qualified staff, and inadequate data-driven decision-making.

Lack of planning to develop strategies towards using big data-driven: Organizations often struggle to align BD initiatives with their overarching business strategies in clear and actionable terms. This misalignment results in fragmented efforts, underutilized resources, and missed opportunities to gain a competitive advantage. Moktadir et al. [13] attempted to evaluate the obstacles to the usage of BDA in Bangladeshi manufacturing supply chains in order to help decision-makers create action plans to overcome them. Sanders [33] created a maturity map for the progression of analytics implementation through four stages: data structuring, data availability, basic analytics, and advanced analytics. Additionally, a framework for integrating BDD into SCM was developed, consisting of three main stages: segmentation, alignment, and measurement. Wang et al. [70] to extrapolate the relationship between the various levels of supply chain analytics (SCAs) maturity to logistics and SCM strategy and operations, a framework for SCA maturity was developed based on various supply chain objectives. It includes five levels: collaborative SCA, process-based SCA, functional SCA, agile SCA, and sustainable SCA. The aim of this framework is to examine and explain the processes that supply chains use to increase their effectiveness. Chalmeta and Barqueros-Muñoz [71] developed a framework for SSCM composed of six dimensions—organization, human resources, methodology, maturity model, stakeholders, methodology, and technology—to support the decision-making process and the project sustainability, the balanced scorecard and BDA are being used to create a sustainable supply chain.

Time Constraints: One of the main problems in managing new projects in manufacturing industries is time constraints [13]. Zhong et al. [14] stated that data may be required by decision-making models to determine solutions for a variety of uses, including analytical levels strategic, and operational. BD installation could be expensive and time-consuming. However, decision models require a lot of computing time when dealing with huge amounts of data [72]. However, over time, the greater competitive edge can exceed its drawbacks. Since Apache Spark (version 3.5.2) can process large amounts of data in memory with fast reaction times, it offers an alternate platform for stream data processing and analysis [73]. Nonetheless, Cloudera offers a versatile approach that accommodates both structured and unstructured data. The Cloudera Enterprise edition guarantees a 7–45 times performance boost for queries that contain at least one join and cuts query response times to seconds. The speedup of even the aggregation queries has been about 20–90 times [74].

No Policy to Share Data Among Organizations: A wide range of stakeholders, including suppliers, designers, clients, contractors, and subcontractors, typically surround the supply chain in the construction sector. Each stakeholder performs independently in the absence of supportive policies for data exchange, which results in fragmented data storage and analysis [75]. Integrability and the analytical potential of data are limited because different stakeholders in a construction project gather and store data in formats and systems that may not be cohesive. Moktadir et al. [13] assisted decision-makers in developing strategic plans related to the application of BDA in supply chains by taking into account the obstacles and recognizing their true nature. Alharthi et al. [35] verified that the existence of sharing policies is a crucial issue for both business development and BDA tool adoption. As a result, decision-makers are encouraged to create manufacturer collaboration policies and companies should therefore pay proper attention to their data-sharing procedures or rules.

Weakness of Data-driven Decision-making in Organizations: Effective business analytics that uses multi-dimensional, comprehensive data that includes the network's dynamic activities, as well as its static characteristics, are essential for decision-making success. Therefore, Long [76] created a four-dimensional supply chain network flow model to satisfy the data-granularity model's needs for decision-making, and for supply chain networks,

a methodology of data-driven decision-making is investigated to standardize the data form for decision-making. Hedgebeth [77] explained how business intelligence is used in enterprise data-driven decision-making and demonstrated how using business intelligence applications helps a knowledge enterprise by increasing organizational efficiency, especially through the use of analytical techniques to offer insightful decision-making skills for reducing operating expenses and precisely predicting market trends. Long [78] created a model that aims to improve a supply chain network's overall performance through decentralized decision-making and cooperation amongst many organizations and proposed an innovative approach for organizing decision-making based on information, time, and material flows.

Lack of Training Facilities: The success of enterprises worldwide depends on regular and proper training [13]. Managers of the company acknowledge that recent technological advancements have altered work procedures, necessitating investments in staff development and training for BDA [79]. Consequently, industrial managers ought to support training initiatives that take BD tools into account. IT staff can gain the necessary degree of expertise and proficiency in using BDA products by supporting training programs, so, this can improve the performance of manufacturing firms in the international market. This obstacle can be lessened by setting up frequent and suitable training sessions [13]. Dehkhodaei et al. [37] claimed that arranging for managers to participate in in-service training programs, sending managers overseas to gain information, and arranging for senior executives of organizations to meet with university professors and experts is the most effective way to improve managers' knowledge and comprehension of BD, in order to encourage senior management of both public and private organizations to act towards lowering obstacles and expanding government support for BD development by educating them about the financial advantages of BDA. Outsourcing is another strategy to address the skills gap after realizing that the company's current workforce is insufficient to meet its demands, hiring would require a significant investment of resources for an uncertain result, and training would be excessively expensive or time-consuming [80].

Lack of Skilled Personnel: One of the major obstacles to implementing BD is the shortage of skilled IT personnel, because, without qualified staff, problems like data entry errors, record loss, and misunderstandings regarding data insight continue to exist [13], which impair decision-making, as seen by the construction supply chains' overall decreased efficiency. Therefore, investing in new technology and human resources, having management adopt new values and continuously adapt, and enhancing employees' abilities and technological adaptability have been the pathways for improvement [79]. Alharthi et al. [35] categorize the necessary BD skills into two groups: primary skills, such as familiarity with BD platforms and technologies (e.g., NoSQL, In-memory DB, MapReduce, Hadoop), and secondary skills, such as machine learning, decision-making models, data visualization, predictive analytics, and expertise of math and statistics. Training programs should also include these secondary skills.

Weak Support from Managers in Implementing New Technologies: Employees frequently hesitate to embrace new technologies, largely because of concerns about potential job loss and uncertainty regarding their performance due to insufficient skills. So, Kusi-Sarpong [81] claimed that by providing specialized training and employing data scientists for data analysis, a skill development strategy can assist organizations in enhancing the analytical skills of their workforce and fostering a culture that is supportive of embracing new technologies. To fulfill company aims and objectives, top management commitment is essential [82]. Liu et al. [83] stated that there are three methods by which top management supports the effects of BD technology adoption: initially, create organizational cultures and strategic policies that encourage the use of BD technologies; second, make hardware,

software, and financial and human resources more accessible; and, lastly, employees may be afraid about being replaced when organizations use BD technology, in addition to having to master new data analysis and visualization techniques. Therefore, if senior executives can inspire staff members and assist them in overcoming psychological obstacles, they are more likely to accept BD technology in these situations.

3.2.4. Regulatory-Related Barriers

Several regulatory barriers hinder the adoption of BDD including shortcomings in governance policy frameworks, inadequate government policies for embracing new technologies, and weak legislation concerning privacy, data security, and intellectual property. These obstacles not only slow down the development of BDD solutions but also generate uncertainties that may discourage stakeholders from investing in innovative technologies.

Weakness of Governance Policies in Support of BD Development: Enterprises consider data governance as a possible strategy to ensure data quality, enhance and utilize information, preserve its worth as a vital organizational resource, and assist in gaining insights for company operations and decision-making [84]. Data governance is something that business intelligence (BI) providers point out as a problem that their clients need to solve, not something that a BI solution can handle [85]. Arunachalam et al. [34] asserted that privacy and security issues can be resolved by implementing an efficient data governance strategy during the data integration and management process. Esfahbodi et al. [86] developed and empirically evaluated an integrated model of governance pressures–SSCM practices–performance with the objective of identifying the role of governance in the adoption of SSCM. Their investigation revealed that the adoption of sustainable techniques to attain SSCM in the manufacturing sector was preceded by exogenous driving forces of governance. Saberi et al. [87] asserted that blockchain dependability and transparency aim to more effectively permit the transfer of information and materials along the supply chain with automated governance regulations because of actor certification and approval. In a blockchain-based supply chain, smart contract governance and process regulations can be utilized to manage both the procedures they may access and need to carry out.

Weakness of Government Policies for New Technology Adoption: Government policies can establish the institutional foundation and principles required for adoption, and thus have a comparatively large impact on how BD is adopted in companies [88]. An incompatible environment might require businesses to either double work or stick with the original format when a technology's adoption is ignored or promoted by the government. The adoption of technologies like BD promotes transparency and improved decision-making, and the general management of digital information should also be supported, encouraged, regulated, and encouraged by governments [89]. Without government support, information technology cannot spread and be used [90]. Since innovations would most likely be developed in a favorable administrative framework, it has been demonstrated that the regulatory environment plays a crucial role in the diffusion of innovations [91]. Small- and medium-sized enterprises (SMEs) find it challenging to adopt BD because of the financial burden and labor scarcity associated with its establishment and execution. Thus, government policies and assistance including BD expert training, consultation, and funding are essential for promoting BD adoption in SMEs [92]. Lai et al. [90] found that government PR, which means that in order for a company to obtain government support, it must implement new technology to enhance the connection between adoption intention and top management support because senior managers are frequently aware of governmental orientation, and they would focus more on reacting official PR calls. The same occurs in competitors' adoption of BDA, which may improve the direct impact of senior management's BDA adoption intention. Wang et al. [93] claimed that by implementing

laws or rules pertaining to data use and protection, tax relief, open data, fiscal subsidies, and employee training, the government may assist firms in lowering the costs associated with implementing new technologies.

Weak Laws in the Areas of Privacy, Data Security, and Intellectual Property: International supply chains may be seriously concerned about privacy, security, and data laws since they must follow local laws while exchanging data [34,94]. Government initiatives including supplying public data, developing specialists, safeguarding intellectual property, and controlling privacy and security will have an impact on enterprises' adoption of BD [88]. Similarly, in both developed and emerging markets, managers' decisions about BD security in the supply chain are influenced by stronger legal requirements [95]. Park and Kim [92] discovered that the development and security of a BD infrastructure might be significantly aided by governments' open data, data usage, and promotion policies by strengthening cooperation in data analysis and securing foreign data. Sivarajah et al. [36] stated that strict compliance with these privacy requirements must be implemented in the data warehouse and that there must be some standard privacy legislation that may regulate the usage of such personal information. Reyes-Veras et al. [89] highlighted security issues as a problem in BD because there is not a formalized procedure in place for protecting the confidentiality of the data. Dehkhodaei et al. [37] claimed that politicians should impose strict laws on intellectual property, privacy, and data security in order for senior managers to move forward with using data in the decision-making process with more confidence, as it is imperative that trust be increased amongst them.

3.2.5. Economic-Related Barriers

Economic barriers significantly hinder the widespread adoption of BDD. These challenges stem from high investment costs, limited awareness of the economic advantages, and the misalignment of existing business models with data-driven practices, which collectively pose substantial obstacles to seamless integration, particularly in the construction sector.

High Cost of Investment: In the construction industry, investment has always been a barrier to the adoption of new technologies since it does not belong to the high-profit margin industries, and after purchasing the technology, there is a training component that costs money [96]. Finding a method to prioritize and justify the continuous investments in technology needed for BDA is an ongoing problem for firms [97]. In particular, BDA investment necessitates significant financial resources for hardware and software development [81] related to staff training, organizational structure changes, equipment and IT infrastructure updates, and continuous expenses associated with the storage and processing of large volumes of data [82] and maintaining infrastructure [98]. Adoption and implementation of technology solutions by organizations may be impacted by the sensitive topic of data processing costs and other data center operating expenses. One major obstacle to using BDA is cost. Manufacturers are opposed to BDA because they are constantly looking for methods to reduce the price of their goods [13]. However, balancing the possible improvements in performance and efficiency against the expense of BD management systems presents a dilemma for managers [95]. Du et al. [99] employed multi-agent systems and RFID technology to improve decision-making and real-time information exchange in the supply chain for prefabricated construction while simultaneously reducing costs by making it possible to accomplish pull manufacturing and reduce the assembler's inventory and delay. The adoption of BD in companies can be facilitated by securing financial investment competence, which will help to overcome the barrier of implementation and operation costs. Effective utilization of budgets and allocation for investment financing is a component of financial investment competency. A thorough examination of BD can

drastically cut down on decision time and computing expense when compared to standard datasets [100].

Lack of Sufficient Knowledge About the Economic Benefits of Big Data-driven: If the management of the company is uncertain about the return on investment, they are reluctant to invest in a novel concept or technological advancement [96]. The benefits of BDA are felt over time; in other words, BDA does not directly boost sales or exports, it is hard to persuade people to invest, particularly when the costs are large, and the payback period is lengthy [82]. Consequently, informing senior managers of both public and commercial organizations about the financial advantages of BDA encourages them to work towards lowering obstacles and boosting government funding for BD development [37]. Nonetheless, one effective way to lower the investment budget is to align company strategies for BD with investment objectives [92], and creating data-driven business models will be helpful in raising the return on investment [101]. Kache and Seuring [97] claimed that by using BDA, companies might save money because unscheduled equipment downtimes could be greatly decreased, enabling companies to reduce buffer inventories, which in turn allows the partners to run a more efficient supply chain while removing supply risks.

Weak Compliance of Business Models with the Subject of Data-driven: Establishing a positive data-driven culture requires a thorough comprehension of the organization's challenges and a suitable level of top management support [102]. Organizations will be reluctant to use BDA for supply chain planning if the implications from existing business cases are unclear, no specific benefit is understood, and also the technology is highly complex [97]. Utilizing BDA effectively is based on the notion that by examining enormous volumes of unstructured data from various sources, insightful information can be discovered and assist companies in changing their business models [103].

4. The Applications of Big Data-Driven in Supply Chain Management

BD is reshaping supply chain management. The Council of Supply Chain Management Professionals (CSCMP) is actively investigating methods to incorporate it into supply chain operations by highlighting the increasing significance of machine learning and advanced data analytics in strengthening the resilience and sustainability of supply chains. Their report indicates that organizations implementing BD have achieved a 10% reduction in costs and an 8% increase in profits. Moreover, McKinsey & Company has emphasized that adopting BDA in the construction industry can reduce project timelines by 10–20% and lower project costs by 5–10%. Artificial intelligence (AI) techniques utilize BD systems to generate actionable insights and critical information even before a project begins. This forward-thinking approach facilitates the early detection and resolution of challenges such as coordination issues on construction sites, conflicts, disputes, and the adverse effects of bad weather. BDA helps minimize delays and reduce material costs by providing accurate and clear data, as well as the early identification of potential structural problems; moreover, BD enables project managers to make well-informed decisions in a short time and reduce the probability of human errors. The incorporation of BD into construction projects offers many advantages, including but not limited to increasing productivity, shortening project timelines, reducing risks, minimizing waste, and improving safety [67]. BD applications in various SCM domains are divided into five main categories: risk management and resilience, supplier management, operations optimization, sustainability, and logistics and transportation, as discussed in the following.

4.1. Risk Management and Resilience

Risk is an inherent part of human activity that can lead to disastrous outcomes including regulatory changes, fluctuating commodity prices, product failures, financial crises,

and natural disasters. Supply chain risks come from internal production processes, suppliers, and customers. The supply chain's overall efficacy is affected by these risks. Risks connected to shortages, legal concerns, quality, compliance, disasters, safety, and security threats must all be identified for effective risk management [104]. Supply chain risks can be divided into two categories: first, operational risks, also known as internal risks, and, second, disruption risks, also recognized as external risks [105]. Wu et al. [106] created an evaluation that, by combining BD and other data sources, assists companies in identifying critical characteristics and improving their comprehension of supply chain uncertainties and risks. This enables them to make accurate, thorough, and logical decisions based on cross-functional considerations. Kara et al. [107] created a framework for the identification, evaluation, and mitigation of various supply chain risks based on data mining. Singh and Singh [108] investigated how companies can establish BDA capabilities inside their organization to increase business risk resilience from supply chain disruption occurrences. The impact of institutional reactions to supply chain disruption events and information technology infrastructure qualifications on the ability of an organization to develop risk resilience from such events was also examined, as was whether BDA mediates these effects. Gupta et al. [109] tested additive manufacturing and BDA to reduce risks and build supply chain resilience in a flexible and control-oriented environment and showed that in the event of a BDA disruption, they can help with risk management, increase a company's supply chain resilience, and reduce the spread of the supply chain ripple impact, which, especially, impacts risk intelligence. Bag et al. [110] investigated how supply chain visibility is directly impacted by BD and predictive analytics capabilities, as well as how these factors ultimately affect community and resource resilience. It was discovered that BD makes it possible for a more effective supply chain monitoring system, which in turn enhances supply chain visibility. Bahrami and Shokouhyar [111] aimed to create and assess a research model to offer new perspectives on the connection between firm performance and BDA capabilities. One of the main conclusions shows that BDA capabilities have a major influence on firm performance and supply chain resilience, and that supply chain resilience acts as a partial mediator in this relationship.

4.2. Supplier Management

Supplier Negotiation: Because buyers and suppliers have different demands and preferences, negotiations are an important means of resolving conflicts and an efficient technique to coordinate the supply chain and cooperate during collaborative procurement [112]. By enhancing negotiation results and offering real-time data and insights for flexible decision-making, the implementation of BDA can assist purchasing departments in performing better [11]. Rozados and Tjahjono [113] demonstrated how BD may assist the supplier negotiation process and claimed that the majority of organizations must make heterogeneous data sources available across functions. Brinch et al. [12] found that BD is commonly utilized as a decision support tool for purchasing and as a source of information to aid in negotiations with suppliers by using a sequential mixed-method approach, which included a Delphi study and a questionnaire survey. Chen and Xu [112] developed a multi-agent system-based negotiation model and proposed a machine learning-based negotiation optimization approach that offers a novel perspective on intelligent supply chain management analysis.

Supplier Evaluation and Selection: In supply chain management, evaluating suppliers is a crucial issue [114]. AI approaches can be used to find potential suppliers by using the data available in digital supply chain systems in supplier selection [115]. Noorizadeh [116] created data-driven techniques utilizing buy transaction data and assessments of performance for supplier development and evaluation in the construction industry. The data

included in the investigation comes from suppliers that worked on Finnish construction between 2010 and 2016 and are employed by a major international construction company. In order to provide a strong tool for determining the different criteria needed for selecting viable suppliers in real-time decision-making and for identifying the best feasible suppliers based on a thorough and data-driven evaluation, a multi-agent system based on BDA was developed by Zekhnini et al. [115] associated with the Distributed Artificial Intelligence theory. Ali and Kassam [117] created a supplier selection methodology that uses a deep learning algorithm to analyze social media customer evaluations to determine the relative relevance of each criterion, followed by a traditional comparison method that relies on expert ratings using the F-AHP approach. Teng et al. [118] developed a framework for the power grid's BDA environment based on an index system and built a method for evaluating material providers that is compatible with the smart grid. This gives the smart grid useful information for choosing green material suppliers.

4.3. Operations Optimization

Demand Planning: The ability to manage operations and processes to satisfy demand and handle changes in both is a vital element of SCM. The ability to convert predictions into capacity demands and precise demand forecasting is essential for efficient capacity planning [70]. The primary objectives of demand forecasting are to optimize inventory, cut expenditures, and enhance revenue, profit, and maintain client relationships [119]. Therefore, a key element of efficacy is the precision of demand forecasts [120]. As a result, many supply chain managers are motivated to use BD to enhance production planning and demand forecasting [121,122]. Wang et al. [123] used randomly generated huge datasets for transportation, warehouse operations, and consumer demand to create a mixed integer nonlinear model that used BD to choose distribution center locations. Feizabadi [124] created a hybrid demand forecasting technique based on neural networks and machine learning to predict demand more accurately by integrating time series models with leading indicators. Kilimci et al. [119] created an intelligent demand forecasting system using several forecasting techniques that were based on the examination and interpretation of historical data, which incorporate deep learning models, time series analysis approaches, support vector regression algorithms, and proposed comprehensive supply chain decision-making procedures.

Inventory Management: Costs can be considerably decreased with effective material supply management [125]. Additionally, in today's supply chain environment, cutting costs by minimizing excess inventory, both staged and in-transit, proactively handling incoming and outgoing events, and pooling assets has become crucial [126]. Tan et al. [127] investigated data-driven inventory decision-making techniques to improve comprehension of how the distinct features of the cloud supply chain impact inventory control procedures.

Cost Management: In order to reduce various expenses and increase the enterprise's profitability, supply chain cost management controls the costs generated in each link of the supply chain [128]. Mandičák et al. [129] examined the effects of using supply chain management and BD concepts on building construction, material delivery schedules, and building costs. Zhang et al. [130] proposed a prefabricated construction assessment model to direct a supply chain with manageable expenses and concentrated on the study of prefabricated CSCM costs in an IoT setting. Wang et al. [128] designed a cost management model for an enterprise supply chain within the framework of BD and integrates a supply chain and a BD platform into the model of an enterprise supply chain system. Li [131] aimed to illustrate using BDA for sustainable development to optimize logistics management is important and how it improves assessment mechanisms for sustainable logistics practices while lowering costs and increasing efficiency.

4.4. Sustainability

Green Supply Chain: Academics and industry professionals have been paying close attention to green supply chain management (GSCM) as environmental consciousness has increased [132]. Construction is one of the worst polluters in the world [133]. In 2018, 39% of process-related carbon dioxide emissions came from the building and engineering sectors [67] and waste materials and rework activities costs account for 35% of construction costs [134]. When environmental risks emerge, decision support systems can be developed using BDA to help in decision-making [135]. Zhao et al. [136] outlined a multi-objective optimization model for a GSCM scheme that depends on a BDA and minimizes the inherent risk caused by economic cost, hazardous materials, and associated carbon emissions. Alkhatib [137] examined how Jordanian BDA capabilities (BDAC) affected green innovation (GI) and green supply chain integration (GSCI) as well as how GSCI mediated the relationship between GI and BDAC. Papadopoulos et al. [138] tested and developed a theoretical framework that uses unstructured BD to explain supply chain networks' resilience for sustainability.

4.5. Logistics and Transportation

Logistics and Transportation: A key element of SCM that guarantees the efficient flow of commodities from suppliers to customers is transportation [139]. Chen et al. [140] presented a novel technique for predicting travel time using massive data gathered from industrial IoT infrastructure named the gradient boosting partitioned regression tree model. After being empirically compared with other computational approaches, the method successfully improves the predictive accuracy of trip time. Peng et al. [141] employed BD technology to examine a supply chain network's integrated transportation planning and retailing optimization problem under various carbon regulatory policies. The uncertainty theory was used to address the ambiguity of BD and identify the parameters in the integrated optimization problem as uncertain variables. Liu [142] used the K-means clustering algorithm to partition customer demand and the delivery area, in order to decrease the repetition of transportation routes, optimize warehouse layout, and allocate logistics resources and to ensure the efficient operation of algorithms on large-scale data a BDA platform Hadoop is used for data storage and processing. Li et al. [143] developed a deep learning and traffic BD-based method for logistics distribution path optimization and road condition prediction.

5. Research Gaps and Future Directions

Although the number of BDD applications in CSCM has been on the increase (as has been discussed in Section 4), the problems detailed in Section 3 are still not fully addressed, resulting in several ongoing gaps.

5.1. Research Gaps

In the following subsections, five categories of data, technology, organizational and human, regulatory, and economic mirroring the barrier taxonomy developed earlier outline the core gaps.

5.1.1. Data-Related Limitations

Because construction projects usually involve a variety of stakeholders, including contractors, subcontractors, suppliers, and owners, data security and privacy emerge as significant concerns. Despite attempts to improve data security by using some new technologies like blockchain, its integration is still difficult and expensive, which prevents broad adoption. In the same context, the fragmented nature of the construction industry, where

stakeholders work with little cooperation and irregular procedures, creates obstacles for data collecting and exchange, which results in delays and inefficient real-time information sharing. When BD systems are unable to handle huge amounts of data effectively in real time, performance and scalability issues arise. Another obstacle of data integration complexity that makes decision-making more difficult because different systems and formats were developed with inconsistent and fragmented information. Although some integration strategies such as BIM or data warehouses are used to address this problem [52], it is still insufficiently utilized due to financial and technical limitations. Data quality is still a persistent problem. The predictive insights are less reliable and precise when they come from incorrect and inaccurate datasets. Although frameworks like data quality assessing and controlling were proposed [60,61], the implementation of quality control mechanisms is still inadequate and restricts the effective use of BDA in CSCM.

5.1.2. Technology-Related Limitations

Using BD in CSCM has significant technical constraints related to infrastructure for storing and transferring data, specific tools, and performance measurement systems. The lack of robust infrastructure for storing and transferring large datasets is a critical barrier that arises from two main reasons: first is that the legacy systems are often incapable of handling the sheer volume and variety of BD, and the second is the limitation on network bandwidth causes delays in real-time data transfer, which impacts negatively on decision-making and analytics. The conventional approach to moving to scalable on-premises or cloud-based solutions is expensive and hinders broad adoption. The other solutions, such as distributed storage frameworks like Hadoop and optimized cloud systems were proposed [63], their implementation often requires substantial investments and technical expertise that many organizations lack. Another limitation is the unavailability of specialized tools tailored to CSCM because of the nature of construction projects that generate diverse and fragmented data from multiple stakeholders, IoT devices, and other sources, most BD tools are not designed for these highly variable workflows. Therefore, developing and customizing tools like BIM and blockchain systems is required to suit construction-specific requirements. Additionally, the absence of advanced performance measurement systems hinders the use of BD effectively because traditional metrics are insufficient for evaluating these dynamic and real-time processes of BDD and decrease the ability to measure the return on investment and the benefits of applying BDD in the firm.

5.1.3. Organizational and Human-Related Limitations

Strategic planning, absence of data-sharing policies, and training are the main and common organizational and human obstacles to implementing BDD. The lack of strategic alignment between BD initiatives and overarching business objectives arises from inadequate frameworks to guide organizations in progressing from basic to advanced analytics. Some frameworks were proposed like a framework for SSCM [71] but their adoption remains limited due to insufficient planning and guidance. Time constraints present another limitation, as the installation and processing of BD systems are time-intensive, particularly in the absence of fast-processing platforms, although tools like Apache Spark and Cloudera offer potential solutions [73,74]. The absence of data-sharing policies among stakeholders in CSCM is a significant barrier because the data will be stored in fragmented systems, which results in limiting its potential integrability. On the other hand, inadequate training facilities and a shortage of skilled personnel hinder organizations from successfully implementing BDD. The lack of efforts and programs to upskill employees in tools like Hadoop, machine learning, and predictive analytics leads to repeat mistakes, decreased productivity, and inefficient decision-making.

5.1.4. Regulatory-Related Limitations

The critical limitation arises from weak governance policies failing to support effective data integration and utilization, which leads to poor data quality. Although frameworks like blockchain-based smart contracts have been proposed to improve governance and ensure transparency, their implementation remains limited due to a lack of automated governance standards and stakeholder adoption [87]. Inadequate government support for BD adoption is another significant challenge for many businesses, especially SMEs, who face financial and resource restrictions that are made worse by the absence of support from the government and tax incentives, which are important for encouraging widespread adoption and reducing operational burdens. Another major barrier faced by CSCM is the insufficient legislation on issues of intellectual property, data security, and privacy. The lack of clear rules on data privacy protection exposes risks of violations and abuses substantially. In addition, the abuse of privacy regulations, the lack of norms, and governmental open data programs reduce organizations' motivation to adopt, implement, and master BD technologies.

5.1.5. Economic-Related Limitations

The cost of investment is a major barrier and has two contributing factors: first, the hardware and software upgrades, IT infrastructure upgrades, and training, and, secondly, the operational costs for data storage and processing are recurrent. These are the costly effects on the construction industry by reducing profit margins. Although there have been proposals for solutions like RFID and multi-agent systems that could lead to optimized inventory and real-time decision-making to reduce costs [99], implementation of such technologies often entails a high cost and expertise that is not always available within organizations. Furthermore, managers often fail to recognize the value of BD practices in the economy, which can delay the returns on investment for BD. These returns are often too delayed to be observed with practical significance, therefore becoming a significant limitation. Payback periods are often long, which likewise makes upfront costs hard to justify. Additionally, the limited conformity of existing business models discourages data-driven approaches. Many companies fail to adapt their processes to benefit from BD insights because they do not understand how it helps them, and the technology seems complicated to them.

5.2. Potential Research Directions

These gaps outline the most promising potential for future research by highlighting six key themes that include data, technology, organizational capability, policy, and economic considerations.

5.2.1. Data Security, Privacy, and Quality

Addressing the concerns about unauthorized access, breaches and quality of interconnected construction supply chain systems could potentially impact the future research path towards developing large-scale and feasible solutions for using BDD in CSCM. This involves researching areas such as the development of blockchain and hybrid architectures, such as combining IPFS with encryption schemes to protect shared data among the parties. At the same time, future research can contribute to enhancing data quality frameworks that make it possible to prevent, identify, and minimize incomplete, inconsistent, and inaccurate data, all in an automated fashion. Further, developing models and methods for real-time data quality assessment to support BDA on fragmented and diverse construction data will ensure its reliability.

5.2.2. Scalable Infrastructure and Tools for CSCM

To address technological obstacles such as scalability and infrastructure, cloud and edge computing solutions should be explored for their effectiveness cost-wise and their adaptability to construction workloads, concentrating on minimizing latency where huge amounts of data are essential to be processed. Furthermore, future studies need to deal with the fragmented and dynamic characteristics of construction projects by integrating BD tools with construction-related systems of construction projects (e.g., BIM, IoT devices, blockchain).

5.2.3. Advancing Performance Measurement Systems

The traditional performance metrics are not always adequate for BDD processes. Therefore, future studies can focus on developing real-time performance measurement systems capable of providing insight into the efficiency and effectiveness of BD applications in SCM. In other words, these systems need to include predictive analytics and visualization tools to give decision-makers the ability to forecast future performance and make appropriate adjustments. Also, these evaluation frameworks for measuring short and long-term benefits of BD adoption can further create motivation for companies to invest in these technologies.

5.2.4. Organizational Transformation and Skill Development

Effective training models to upskill personnel in BDA, particularly in non-technical roles, is one of the areas that most need to be improved by exploring cost-efficient methods such as e-learning platforms, gamified training modules, and partnerships between academia and industry to provide targeted practical training. So, research should examine organizational change management strategies to address resistance to technology adoption, including how managerial support, incentives, and a culture of innovation can influence successful implementation.

5.2.5. Government Policies and Regulatory Frameworks

The impact of governmental policies and regulatory frameworks on the adoption of BD in CSCM should be the subject of future research, with a focus on the financial incentives in relation to the enforcement of conformance in standardization processes on security protocols and data sharing. In addition, national regulations can foster international collaboration and reduce uncertainty for global constructing supply chains.

5.2.6. Economic Feasibility

Due to financial limitations, it is essential to investigate new strategies for adopting BD while reducing costs. In other words, future research should also aim at improving economic feasibility regarding the optimization of unit costs and long-term reasonable benefits. This includes developing scalable and cost-effective technologies like cloud computing and multi-agent systems, to reduce upfront investment and operational overheads. Indeed, there has been interesting research on the financial return on the investment of big data in the construction supply chain and quantifying how analytics can optimize utilization, decrease downtime, and enhance decision-making needed to be measured.

6. Conclusions

With the rapid development of BD techniques, big data's incorporation in the construction supply chain has started a revolution. It can increase productivity and help with better decision-making, coordination, and collaboration on projects. In this study, we conducted a survey based on 62 publications related to using BD driven in CSCM. Using PRISMA

guidelines, bibliometric tools, and thematic analysis, the research synthesized key trends, applications, and challenges within the domain, covering 62 selected publications from 2014 to 2024. Consequently, a framework of BD in CSCM was presented showing various challenges that need to be handled. The findings revealed that implementation of BDD within CSCM is hindered by a complex set of barriers. There are five challenges that will be met from conventional CSCM to BDD-CSCM; data, technology, organizational and human, regulatory, and economic challenges with a total of 21 specific barriers were identified and discussed, supported by the recent literature and case examples. In response to these obstacles, the study proposed a structured implementation framework offering a practical pathway for the integration of BDD into CSCM to take advantage of transformative benefits such as enhancing decision-making, real-time analytics, improving efficiency, and sustainable practices. Moreover, the study highlighted the key applications of BDD, including risk management, supplier evaluation, sustainability, and logistics.

Despite growing academic interest and technological advancements, significant gaps remain in performance measurement systems, scalable infrastructure, skilled workforce development, and supportive regulatory frameworks. Therefore, future research must give priority to creating data governance frameworks, solutions for improving scalability infrastructure, and customizing tools suitable for the fragmentation nature of the construction industry. Additionally, to improve and leverage BDA, a standard performance measurement system can be developed, and training programs and initiatives to help improve the skills of workers should be implemented. Furthermore, collaboration among policymakers, stakeholders, practitioners, and researchers is essential to harmonize regulatory frameworks and introduce incentives encouraging SMEs to support these technologies. Also, this collaboration can address these limitations and generate research paths for involving BD in the construction supply chain. Therefore, future studies should focus on improving collaboration among stakeholders. Investment has frequently served as an obstacle towards the adoption of new technologies, and since BDA investment requires substantial cost reserves for the development of software and hardware, future research should also focus on enhancing the economic viability of adopting BDD in CSCM. Also, it is important to explore how BDD can be effectively integrated into international construction supply chains to address cross-border challenges such as data interoperability, regulatory disparities, and global coordination among stakeholders.

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Abbreviations

The following abbreviations are used in this manuscript:

AI	Artificial intelligence
BD	Big data
BDA	Big data analysis
BDAC	Big data analysis capabilities
BDD	Big data-driven
BI	Business intelligence
BIM	Building information modeling
CSCM	Construction supply chain management
CSCMP	Supply chain management professionals
DQAC	Data quality assessing and controlling
EIDP	Enterprise integrated data platform
GI	Green innovation
GSCI	Green supply chain integration
GSCM	Green supply chain management
HDFS	Hadoop distributed file system
IoT	Internet of Things
IPD	Integrated project delivery
IPFS	Interplanetary file system
IT	Information technology
KPIS	Key performance indices
PRISMA	Preferred reporting items for systematic reviews and meta-analyses
RFID	Radio-frequency identification
SCA	Supply chain analytics
SCM	Supply chain management
SMES	Small- and medium-sized enterprises

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