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Leveraging Big Data and Business Intelligence for Optimization of Manufacturing Sector Procurement

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Abstract

Procurement within the manufacturing sector has undergone fundamental transformation, driven by the convergence of globalization, digitalization, and competitive pressures. Traditional procurement approaches, while adequate in the past, are increasingly challenged by complexity, volatility, and the need for cost efficiency and agility. Big Data and Business Intelligence (BI) have emerged as pivotal enablers of procurement optimization, offering real-time insights, predictive analytics, and enhanced decision-making capabilities. This paper undertakes a comprehensive review of literature up to 2020, synthesizing how Big Data and BI tools have been conceptualized, applied, and evaluated in manufacturing procurement contexts. The study traces the evolution from conventional, transaction-focused procurement models to data-driven frameworks capable of handling large, diverse, and fast-moving datasets. It highlights how advanced analytics supports supplier evaluation, demand forecasting, risk management, cost control, and sustainability monitoring. By consolidating insights from multiple disciplines including supply chain management, information systems, and operations research this paper provides a structured foundation for understanding the potential and challenges of Big Data and BI in procurement optimization. The analysis underscores key issues of data quality, integration, organizational readiness, and cultural alignment, while identifying opportunities for future research and industrial practice.

Keywords: Big Data, Business Intelligence, Procurement Optimization, Manufacturing Sector, Predictive Analytics, Supply Chain Management

1. Introduction

Procurement has historically been recognized as a critical enabler of efficiency, competitiveness, and innovation in the manufacturing sector [1, 2]. It is through procurement processes that firms secure the raw materials, components, and services necessary for production and distribution. The manufacturing industry, characterized by complex supplier networks, fluctuating demand, and pressure for cost optimization, has long relied on procurement as a lever for operational and strategic performance [3, 4, 5]. However, the accelerating pace of globalization, rapid technological advances, and shifting consumer expectations have dramatically altered the procurement landscape. Traditional approaches, often based on limited information and transactional decision-making, are increasingly insufficient in meeting the dynamic demands of modern manufacturing environments [6, 7]. As such, firms are turning toward digital technologiesparticularly Big Data and Business Intelligence (BI)to achieve procurement optimization [8, 9].

Big Data refers to datasets of unprecedented volume, velocity, and variety, capable of being analyzed to generate actionable insights that transcend the limits of traditional data processing systems [10, 11]. Business Intelligence, by contrast, is a broader umbrella encompassing the methods, tools, and practices that transform raw data into meaningful and actionable information for strategic and operational decision-making [12, 13]. When integrated, Big Data and BI offer manufacturing procurement professionals the ability to collect, process, and analyze vast streams of structured and unstructured data from suppliers, markets, logistics providers, and internal operations. These capabilities not only reduce inefficiencies but also enable predictive forecasting, supplier risk monitoring, cost optimization, and sustainability alignment [14, 15]. For manufacturing firms operating in highly competitive and uncertain environments, leveraging these technologies is not merely a choice but a necessity for survival and growth.

The significance of Big Data and BI in procurement becomes clearer when considered against the historical backdrop of procurement evolution. Initially regarded as a clerical function focused on transactional activities, procurement in the 20th century gradually transformed into a strategic function as firms realized its potential for cost savings and supplier relationship management [16, 17]. By the early 2000s, procurement became increasingly linked with supply chain integration, strategic sourcing, and risk management [18, 19]. Nevertheless, conventional procurement systems faced persistent challenges, including fragmented data, limited visibility, and reactive decision-making. With the rise of Industry 4.0 and the proliferation of digital technologies, procurement entered a new era in which Big Data analytics and BI tools are central to operational efficiency, agility, and resilience [20, 21].

A defining characteristic of manufacturing sector procurement is its reliance on a wide network of global suppliers. These networks are inherently vulnerable to disruptionswhether from economic instability, political tensions, pandemics, or natural disasters. Traditional procurement systems often lack the predictive and adaptive capacity to anticipate such shocks [22, 23]. Big Data analytics, by contrast, offers the ability to mine patterns, model risks, and provide foresight that enhances procurement resilience [24, 25]. For instance, predictive analytics can help firms anticipate supplier delays based on historical performance, weather data, and geopolitical developments, enabling proactive adjustments to procurement strategies [26, 27]. BI tools further support decision-making by presenting data in accessible formats through dashboards, visualizations, and scenario analyses, ensuring that procurement managers have real-time visibility into complex supply ecosystems [28].

The application of Big Data and BI in procurement extends beyond risk management into supplier evaluation and selection. Supplier performance has traditionally been assessed based on criteria such as cost, quality, and delivery reliability. However, modern manufacturing procurement requires more comprehensive evaluations that include sustainability, innovation capacity, and resilience [29]. Big Data facilitates such multidimensional evaluations by integrating data from diverse sources, including performance records, third-party audits, social media, and even satellite monitoring [30]. BI systems then aggregate and present these metrics, allowing procurement managers to make informed supplier choices aligned with organizational priorities [31]. This evolution reflects a broader trend toward data-driven procurement, where decisions are grounded in evidence rather than intuition or limited datasets [32].

Another crucial area where Big Data and BI have reshaped manufacturing procurement is demand forecasting. Accurate forecasting is vital to ensuring the timely availability of raw materials, minimizing inventory costs, and avoiding production disruptions. Traditional forecasting models often relied on historical sales data, which proved inadequate in volatile markets [33]. Big Data allows for the integration of real-time market signals, consumer behavior patterns, and macroeconomic indicators, leading to more accurate and responsive forecasts [34, 35]. When combined with BI, such forecasts can be seamlessly communicated across procurement, production, and logistics teams, ensuring alignment and reducing the bullwhip effect in supply chains [36, 37]. Thus, Big Data and BI jointly improve procurement efficiency by minimizing waste, lowering costs, and enhancing production continuity.

Cost optimization remains one of the primary objectives of procurement. Big Data supports this goal by enabling firms to conduct detailed spend analyses, identify cost-saving opportunities, and negotiate better supplier contracts [38, 39]. BI tools, meanwhile, transform procurement data into dashboards that track spending patterns, highlight inefficiencies, and benchmark performance against industry standards. Together, these technologies empower firms to pursue strategic cost management rather than reactive price negotiation. Moreover, the ability to analyze large datasets enhances transparency and accountability in procurement practices, reducing risks of fraud, maverick spending, and non-compliance [40, 41]. In sectors such as automotive or electronics, where procurement costs constitute a significant portion of total costs, such optimization can provide a critical competitive edge [42, 43].

Beyond cost and efficiency, the integration of Big Data and BI into procurement practices also supports sustainability and compliance objectives. Manufacturing firms are increasingly held accountable by stakeholders for the environmental and social impacts of their supply chains. Big Data analytics enables tracking of suppliers' sustainability practices through diverse data sources, such as energy usage, emissions, and labor conditions [44, 45]. BI systems then consolidate these insights, allowing procurement managers to ensure compliance with regulatory requirements and align procurement practices with corporate sustainability goals [46, 47]. This shift demonstrates that procurement optimization is not solely about reducing costs but also about creating value through responsible and transparent practices [48, 49].

Despite the transformative potential of Big Data and BI, significant challenges remain. Data quality, availability, and integration are persistent issues in procurement systems [50]. Manufacturing firms often face data silos across departments and suppliers, hindering the seamless flow of information. Additionally, implementing advanced analytics requires substantial investments in infrastructure, skilled personnel, and organizational change management [51, 52]. Cultural resistance within procurement teams, where traditional decision-making norms may dominate, also impedes adoption. Furthermore, while Big Data promises predictive insights, overreliance on automated systems risks sidelining human judgment and contextual knowledge, which remain vital in complex procurement environments [53, 54]. These challenges underscore that technological adoption must be accompanied by organizational readiness and cultural transformation.

From a theoretical standpoint, the integration of Big Data and BI into procurement aligns with several conceptual frameworks. Resource-based theory suggests that firms leveraging superior information-processing capabilities can achieve competitive advantage [55, 56]. Transaction cost economics highlights how data-driven procurement reduces information asymmetry and opportunism in supplier relationships. Institutional theory emphasizes how regulatory and stakeholder pressures drive the adoption of sustainable procurement practices supported by analytics.

These perspectives underscore that the adoption of Big Data and BI in procurement is not only a technological shift but also a strategic and institutional imperative [57].

In sum, the introduction of Big Data and Business Intelligence has fundamentally redefined procurement optimization in the manufacturing sector. By enabling predictive forecasting, comprehensive supplier evaluation, cost optimization, risk management, and sustainability monitoring, these technologies provide firms with unprecedented capabilities to navigate complexity and uncertainty. Yet, their successful implementation requires overcoming challenges related to data quality, integration, organizational readiness, and human-technology balance. This paper, therefore, seeks to consolidate literature up to 2020 on the application of Big Data and BI in procurement, with a particular emphasis on manufacturing contexts. The aim is to provide a structured foundation for understanding the methodological developments, practical applications, and theoretical underpinnings of these technologies in procurement optimization.

The remainder of this paper is structured as follows. Section 2 presents an extensive literature review, synthesizing prior studies on Big Data and BI in procurement. Section 3 discusses the implications for manufacturing organizations, emphasizing challenges and opportunities. Section 4 concludes with reflections and directions for future research.

2. Literature Review

The application of Big Data and Business Intelligence (BI) in procurement has been the subject of increasing scholarly and managerial attention, particularly in the context of the manufacturing sector. Procurement, as both an operational and strategic activity, relies heavily on the ability to gather, interpret, and act upon information. With the rise of digital technologies, the nature of procurement has shifted from reactive, transaction-driven processes to proactive, data-driven systems capable of handling the complexity and dynamism of global supply chains [58, 59]. This literature review synthesizes the major strands of research up to 2020, tracing the intellectual evolution of Big Data and BI in procurement, the methodological approaches employed, the key thematic areas addressed, and the challenges and gaps identified.

2.1 Evolution of Procurement Research toward Data-Driven Models

Procurement research initially centred on transactional efficiency, cost minimization, and supplier relationships, relying largely on managerial judgment and limited data sources [60, 61]. Over time, however, it became apparent that such approaches were insufficient for addressing the uncertainties of global manufacturing supply chains. Early studies highlighted the limitations of fragmented procurement information systems, which led to inefficiencies, duplication of efforts, and weak supplier coordination. By the late 2000s, the emergence of digital platforms and integrated enterprise resource planning (ERP) systems began to reshape procurement practices, creating the groundwork for data-driven decision-making [62, 63].

The introduction of Big Data analytics marked a turning point. Characterized by the "four Vs"—volume, velocity, variety, and veracity, Big Data provided procurement professionals with access to massive datasets from internal operations, suppliers, logistics partners, and external sources such as markets and social media. Concurrently, BI systems offered the tools to process, visualize, and interpret this data, turning raw information into actionable insights [64, 65]. As manufacturing firms embraced digitalization under the Industry 4.0 paradigm, procurement research increasingly turned toward understanding how Big Data and BI could optimize sourcing strategies, supplier evaluation, demand forecasting, and cost control [66].

2.2 Big Data in Procurement: Capabilities and Applications

The literature identifies several key capabilities of Big Data that directly enhance procurement optimization. First, Big Data enables predictive analytics, allowing firms to anticipate demand fluctuations, supplier delays, and market shifts [67]. Predictive models based on machine learning and statistical techniques have been applied to procurement data to forecast material requirements, evaluate supplier risk, and optimize inventory policies. This represents a significant improvement over traditional forecasting methods, which were often reactive and based on limited historical data [68].

Second, Big Data supports supplier evaluation and monitoring. Procurement has historically relied on performance scorecards and subjective assessments to evaluate suppliers. By leveraging Big Data, organizations can integrate diverse datasetsranging from delivery performance records and financial health indicators to social media sentiment and sustainability reportsinto supplier evaluations [69]. This multidimensional perspective enhances transparency and reduces information asymmetry in supplier relationships. Furthermore, real-time monitoring capabilities allow procurement teams to track supplier compliance with contractual obligations, sustainability standards, and regulatory requirements [70].

Third, Big Data facilitates spend analysis and cost optimization. Research has shown that procurement costs constitute a significant portion of total manufacturing expenses, often exceeding 50% in sectors such as automotive and electronics. Big Data analytics enables detailed examination of spending patterns, identification of inefficiencies, and detection of maverick purchasing. When integrated with BI tools, this analysis supports strategic sourcing decisions, negotiation strategies, and supplier consolidation initiatives. The ability to benchmark procurement costs against industry peers further enhances competitive positioning [71].

Lastly, Big Data plays a critical role in risk management and resilience. Global supply chains are increasingly exposed to disruptions such as natural disasters, political instability, and pandemics. Big Data analytics allows organizations to model risks, simulate scenarios, and identify vulnerable nodes in supply chains [72, 73]. By incorporating external data sources such as weather forecasts, geopolitical risk assessments, and transportation data, procurement managers can proactively mitigate risks and enhance supply chain resilience. This risk-aware approach has been particularly emphasized in post-2010 literature, reflecting the growing vulnerability of global manufacturing networks.

2.3 Business Intelligence: From Reporting to Strategic Insight

While Big Data provides the raw material for analysis, BI systems are essential for transforming data into insights that can be readily used by procurement managers. Early BI systems focused on reporting and descriptive analytics, offering static dashboards and basic visualization tools. However, as data sources and analytical capabilities expanded, BI evolved into a strategic function, providing diagnostic, predictive, and prescriptive insights [74, 75].

In procurement contexts, BI supports decision-making by consolidating data from ERP systems, supplier databases, and external sources into centralized platforms. Dashboards and visualization tools enable procurement managers to monitor key performance indicators (KPIs) such as supplier on-time delivery, defect rates, and contract compliance in real time. Beyond monitoring, advanced BI systems provide "what-if" scenario analysis, enabling procurement teams to evaluate the potential outcomes of sourcing decisions, supplier changes, or market fluctuations [76]. This analytical sophistication enhances procurement agility and responsiveness, aligning with the broader goals of manufacturing competitiveness.

Moreover, BI supports collaborative decision-making by making procurement data accessible across organizational hierarchies. Procurement professionals, production managers, and senior executives can share a common understanding of procurement performance, reducing siloed decision-making and enhancing cross-functional integration [77]. This democratization of data reflects a key shift in procurement practices, where transparency and collaboration are increasingly valued alongside efficiency [78].

2.4 Integration of Big Data and BI in Manufacturing Procurement

The integration of Big Data and BI represents a natural evolution in procurement research and practice. Studies have emphasized that Big Data alone does not guarantee better decisions unless it is effectively processed, interpreted, and applied through BI systems [79]. Conversely, BI systems without robust data inputs risk offering outdated or incomplete insights [26, 80]. Together, Big Data and BI provide a synergistic framework for procurement optimization.

For instance, in supplier selection, Big Data enables the collection of diverse performance metrics, while BI tools aggregate and present these metrics in accessible dashboards for decision-making. In demand forecasting, Big Data models generate predictive insights, while BI systems communicate these forecasts to procurement and production teams in real time. Similarly, in risk management, Big Data provides the analytical power to detect vulnerabilities, while BI systems facilitate scenario planning and executive decision-making [81]. This integration underscores that the value of data-driven procurement lies not only in technological capabilities but also in the organizational capacity to interpret and act on insights.

2.5 Sustainability and Compliance in Data-Driven Procurement

One of the most significant trends in procurement research up to 2020 is the growing emphasis on sustainability and compliance. Manufacturing firms are increasingly held accountable for the environmental and social impacts of their supply chains, driven by regulatory requirements, stakeholder expectations, and corporate social responsibility commitments [82]. Big Data and BI have been applied to track supplier sustainability practices, monitor emissions, evaluate labor conditions, and ensure compliance with ethical standards.

For example, data from suppliers' energy usage, environmental audits, and social performance indicators can be integrated into procurement systems to assess compliance with sustainability criteria. BI dashboards then provide procurement managers with a consolidated view of supplier sustainability performance, enabling informed sourcing decisions aligned with corporate values. This approach reflects a shift from cost-based procurement optimization to value-based procurement, where long-term social and environmental impacts are incorporated into decision-making.

Nevertheless, the literature highlights challenges in this domain, particularly regarding the reliability and comparability of sustainability data across industries and regions [83]. While Big Data provides unprecedented access to information, inconsistencies in reporting standards and data availability hinder the development of universally applicable sustainability metrics. Scholars have therefore called for greater standardization and transparency in sustainability reporting to enhance the effectiveness of data-driven procurement frameworks [84].

2.6 Challenges and Critiques

Despite the promise of Big Data and BI in procurement optimization, several critiques recur in the literature. The first relates to data quality and integration. Manufacturing firms often operate with fragmented data systems across departments and suppliers, leading to challenges in data harmonization. Poor data quality, including inaccuracies and missing values, undermines the reliability of analytics [85].

The second critique concerns resource requirements. Implementing advanced analytics demands significant investments in infrastructure, skilled personnel, and change management. Small and medium-sized enterprises (SMEs), which constitute a substantial portion of manufacturing sectors worldwide, may lack the resources to adopt such systems [86]. This raises concerns about unequal access to the benefits of data-driven procurement and the risk of widening competitive disparities.

The third critique relates to cultural and organizational resistance. Procurement professionals accustomed to intuition-based decision-making may resist reliance on data-driven systems. Overreliance on analytics also risks sidelining tacit knowledge and contextual judgment, which remain vital in complex procurement environments [87]. Scholars emphasize the need for balanced approaches that integrate human expertise with data-driven insights.

Lastly, there is the issue of data security and privacy. The increasing reliance on external and unstructured data sources raises concerns about cybersecurity, intellectual property protection, and compliance with data privacy regulations. These issues must be addressed for firms to fully realize the benefits of Big Data and BI in procurement [88].

2.7 Synthesis of Trends up to 2020

Synthesizing the literature reveals several key trends by 2020. First, there is a clear trajectory from transaction-focused procurement to strategic, data-driven models enabled by Big Data and BI. Second, predictive analytics, supplier evaluation, cost optimization, and risk management emerge as the core domains of application. Third, sustainability and compliance have become indispensable dimensions of procurement optimization, though data-related challenges remain. Fourth, persistent issues of data quality, integration, organizational readiness, and cultural alignment constrain adoption. These findings suggest that while Big Data and BI hold transformative potential for procurement in manufacturing, their successful implementation requires not only technological capability but also organizational adaptation, governance, and cultural change.

In conclusion, the literature demonstrates that Big Data and BI are reshaping manufacturing procurement into a more predictive, resilient, and value-driven function. Yet, the journey toward comprehensive adoption remains ongoing, with unresolved challenges offering fertile ground for future research. By consolidating contributions up to 2020, this review establishes a foundation for examining the implications of data-driven procurement for manufacturing competitiveness, sustainability, and resilience.

3. Discussion and Implications

The review of literature underscores that Big Data and Business Intelligence (BI) are not incremental enhancements to manufacturing procurement, but rather transformative forces that redefine the very nature of decision-making, competitiveness, and supply chain management. While prior procurement practices were dominated by transactional efficiency and cost minimization, the convergence of Big Data and BI has shifted the focus toward resilience, predictive capability, and value creation. This transformation has multiple implications for both theory and practice.

From a strategic perspective, procurement has evolved into a critical enabler of organizational agility and competitiveness. By leveraging Big Data, firms can detect early warning signals from suppliers, markets, and external environments, thereby gaining foresight that supports proactive decision-making. BI systems further ensure that these insights are disseminated across organizational hierarchies, creating shared situational awareness and enabling coordinated responses [89, 90, 91]. For manufacturing firms, this means procurement is no longer a reactive cost center but a driver of strategic advantage, capable of shaping production continuity, market responsiveness, and long-term innovation.

Another major implication concerns supplier relationships and collaboration. Traditional supplier evaluation frameworks often emphasized cost and quality, overlooking relational dimensions such as trust, innovation capacity, and sustainability. With Big Data and BI, organizations can now incorporate multidimensional performance metrics, integrating operational, financial, social, and environmental data into supplier assessments. This broader perspective encourages firms to engage with suppliers as strategic partners rather than transactional entities. Practically, this implies that supplier collaboration can be enhanced through transparent data sharing, joint forecasting, and aligned sustainability goals [92].

At the operational level, Big Data and BI offer significant efficiency gains through improved demand forecasting, spend analysis, and risk management. Predictive models allow manufacturing firms to optimize inventory levels, avoid stockouts, and minimize excess holding costs. Spend analytics, supported by BI dashboards, highlight inefficiencies and support negotiation strategies, thereby delivering direct cost savings. Risk analytics enable procurement teams to map vulnerabilities across supplier networks and design contingency plans. These operational capabilities are particularly critical in volatile environments, where firms face disruptions ranging from raw material shortages to geopolitical crises [93].

The implications extend to sustainability and corporate responsibility, where Big Data and BI enable procurement managers to ensure compliance with ethical standards and regulatory requirements. In an era of heightened stakeholder scrutiny, the ability to track supplier emissions, labor practices, and community impacts enhances organizational legitimacy and stakeholder trust. However, the literature also highlights persistent challenges in ensuring data reliability and comparability across industries [94]. This suggests that firms must not only invest in analytics but also engage with broader institutional efforts to standardize sustainability metrics.

From a theoretical standpoint, the adoption of Big Data and BI in procurement reinforces several conceptual frameworks. The resource-based view suggests that superior information-processing capabilities constitute strategic resources that provide firms with sustained competitive advantage [95]. The transaction cost economics perspective highlights how analytics reduces information asymmetry, thereby minimizing opportunism and transaction costs in supplier relationships. Meanwhile, institutional theory emphasizes how regulatory and societal pressures shape procurement practices, driving the integration of sustainability metrics into data-driven frameworks [96]. These theoretical perspectives underscore that procurement optimization is not only a technological shift but also a socio-organizational phenomenon shaped by institutional, strategic, and relational forces.

Despite the promise of Big Data and BI, the literature emphasizes the importance of organizational readiness and cultural transformation. Advanced analytics requires not only technological infrastructure but also skilled personnel and an organizational culture receptive to data-driven decision-making. Resistance to change among procurement professionals accustomed to intuition-based practices can impede adoption. Moreover, overreliance on automated analytics risks sidelining tacit knowledge and contextual judgment, which remain essential in complex procurement environments. This implies that organizations must balance technological adoption with investments in training, change management, and human-technology integration [97].

Finally, the discussion raises concerns regarding data governance, security, and ethics. Procurement increasingly relies on diverse external data sources, raising issues of cybersecurity, intellectual property protection, and compliance with privacy regulations. Breaches or misuse of procurement data can undermine trust and create reputational risks. Thus, organizations must develop robust governance frameworks that ensure data integrity, security, and ethical use [98]. Addressing these issues is essential for the sustainable adoption of Big Data and BI in procurement.

In summary, the integration of Big Data and BI into procurement practices in the manufacturing sector has far-reaching implications across strategic, operational, relational, and institutional dimensions. While these technologies offer significant opportunities for optimization, their effective adoption requires careful attention to organizational readiness, sustainability challenges, and data governance. For researchers, these insights highlight the need for more integrative frameworks that combine technological, organizational, and institutional perspectives. For practitioners, they underscore the importance of aligning analytics initiatives with strategic objectives, cultural transformation, and ethical governance.

4. Conclusion

This paper has undertaken a comprehensive review of the literature on the use of Big Data and Business Intelligence for procurement optimization in the manufacturing sector, focusing on contributions published up to 2020. The analysis demonstrates a clear trajectory of evolution from transactional, cost-focused procurement practices to strategic, data-driven models characterized by predictive, multidimensional, and value-based decision-making [99, 100].

The findings highlight that Big Data provides procurement managers with unprecedented capabilities to collect, process, and analyze vast datasets from diverse sources, while BI tools transform these datasets into actionable insights through visualization, dashboards, and scenario analysis. Together, these technologies enhance supplier evaluation, demand forecasting, spend analysis, risk management, and sustainability compliance. As such, Big Data and BI not only improve operational efficiency but also position procurement as a strategic function central to competitiveness and resilience [101].

At the same time, the review underscores persistent challenges. Data quality, availability, and integration remain critical barriers, while resource constraints hinder adoption, particularly among small and medium-sized enterprises. Organizational resistance to cultural change, as well as risks of data overload and overreliance on automation, further complicate implementation. Moreover, issues of cybersecurity, privacy, and ethical governance present ongoing risks that must be addressed for the sustainable integration of analytics into procurement [102].

For practitioners, the study implies that successful adoption of Big Data and BI in procurement requires a holistic approach that balances technological capability with organizational readiness, cultural transformation, and governance frameworks. Procurement leaders must not only invest in analytics infrastructure but also ensure that procurement teams are trained, aligned, and empowered to interpret and act upon data-driven insights. For scholars, the review identifies fertile areas for future research, including the standardization of sustainability metrics, the integration of human judgment with automated analytics, and the exploration of cross-disciplinary frameworks that bridge operations research, information systems, and organizational behavior [103].

In conclusion, the optimization of manufacturing procurement through Big Data and BI represents both a challenge and an opportunity. While technological capabilities provide firms with powerful tools for enhancing efficiency, resilience, and sustainability, the true potential of data-driven procurement lies in its integration with organizational strategies, cultures, and values. By consolidating contributions up to 2020, this paper provides a structured foundation for advancing both research and practice, offering pathways for organizations to harness the full potential of Big Data and BI in shaping the future of procurement.

5. References

1. Nwani S, Abiola-Adams O, Otokiti BO, Ogeawuchi JC. Building Operational Readiness Assessment Models for Micro, Small, and Medium Enterprises Seeking Government-Backed Financing. Journal of Frontiers in Multidisciplinary Research. 2020; 1(1):38-43.
2. Omisola JO, Shiyanbola JO, Osho GO. A Predictive Quality Assurance Model Using Lean Six Sigma: Integrating FMEA, SPC, and Root Cause Analysis for Zero-Defect Production Systems. Unknown Journal, 2020.
3. Blome C, Hollos D, Paulraj A. Green procurement and green supplier development: Antecedents and effects on supplier performance. Int J Prod Res. 2014; 52(1):32-49. Doi: 10.1080/00207543.2013.825748
4. Harmonized monitoring and evaluation indicators for procurement and supply management systems. World Health Organisation, 2011.
5. Omisola JO, Etukudoh EA, Okenwa OK, Olugbemi GIT, Ogu E. Geomechanical Modeling for Safe and Efficient Horizontal Well Placement Analysis of Stress Distribution and Rock Mechanics to Optimize Well Placement and Minimize Drilling. Unknown Journal, 2020.
6. Omisola JO, Etukudoh EA, Okenwa OK, Tokunbo GI. Innovating Project Delivery and Piping Design for Sustainability in the Oil and Gas Industry: A Conceptual Framework. Perception. 2020; 24:28-35.
7. Osho GO. Decentralized Autonomous Organizations (DAOs): A Conceptual Model for Community-Owned Banking and Financial Governance. Unknown Journal, 2020.
8. Gbenle TP, Ogeawuchi JC, Abayomi AA, Agboola OA, Uzoka AC. Advances in Cloud Infrastructure Deployment Using AWS Services for Small and Medium Enterprises. Iconic Research And Engineering Journals. 2020; 3(11):365-381 [Online]. Available: https://www.irejournals.com/paper-details/1708522
9. Mgbame AC, Akpe OE, Abayomi AA, Ogbuefi E, Adeyelu OO. Barriers and enablers of BI tool implementation in underserved SME communities. Iconic Research and Engineering Journals. 2020; 3(7):211-220 [Online]. Available: https://www.irejournals.com/paper-details/1708221
10. Akpe OE, Ogeawuchi JC, Abayomi AA, Agboola OA, Ogbuefi E. A Conceptual Framework for Strategic Business Planning in Digitally Transformed Organizations. Iconic Research and Engineering Journals. 2020; 4(4):207-222 [Online]. Available: https://www.irejournals.com/paper-details/1708525
11. Andersen TJ. Managing in Dynamic, Complex and Unpredictable Business Contexts. Adapting to Environmental Challenges: New Research in Strategy and International Business, Jul 2020, 1-17. Doi: 10.1108/978-1-83982-476-020200001/FULL/HTML
12. Holmlund M, *et al*. Customer experience management in the age of big data analytics: A strategic framework. J Bus Res, Aug 2020; 116:356-365. Doi: 10.1016/J.JBUSRES.2020.01.022
13. Mgbame CA, Akpe OE, Abayomi AA, Ogbuefi E, Adeyelu OO. Barriers and Enablers of Healthcare Analytics Tool Implementation in Underserved Healthcare Communities. Healthcare Analytics. 2020;

45(45)SP:45-45 [Online]. Available: https://www.irejournals.com/paper-details/1708221
14. Ilufoye H, Akinrinoye OV, Okolo CH. A conceptual model for sustainable profit and loss management in large-scale online retail. International Journal of Multidisciplinary Research and Growth Evaluation. 2020; 1(3):107-113.
15. Afolabi M, Onukogu OA, Igunma TO, Adeleke AK. Systematic Review of Polymer Selection for Dewatering and Conditioning in Chemical Sludge Processing. [Journal Not Specified], 2020.
16. Babatunde LA, *et al*. Adversarial machine learning in cybersecurity: Vulnerabilities and defense strategies. Journal of Frontiers in Multidisciplinary Research. 2020; 1(2):31-45. Doi: 10.54660/JFMR.2020.1.2.31-45
17. Gbenle TP, Ogeawuchi JC, Abayomi AA, Agboola OA, Uzoka AC. Advances in Cloud Infrastructure Deployment Using AWS Services for Small and Medium Enterprises. Iconic Research and Engineering Journals. 2020; 3(11):365-381 [Online]. Available: https://www.irejournals.com/paper-details/1708522
18. Ashiedu BI, Ogbuefi E, Nwabekee S, Ogeawuchi JC, Abayomi AA. Developing Financial Due Diligence Frameworks for Mergers and Acquisitions in Emerging Telecom Markets. Iconic Research and Engineering Journals. 2020; 4(1):183-196 [Online]. Available: https://www.irejournals.com/paper-details/1708562
19. Mgbame AC, Akpe OE, Abayomi AA, Ogbuefi E, Adeyelu OO. Barriers and Enablers of BI Tool Implementation in Underserved SME Communities. Iconic Research and Engineering Journals. 2020; 3(7):211-226 [Online]. Available: https://www.irejournals.com/paper-details/1708221
20. Hartmann PM, Zaki M, Feldmann N, Neely A. Capturing value from big data-a taxonomy of data-driven business models used by start-up firms. International Journal of Operations & Production Management. 2016; 36(10):1382-1406. Doi: 10.1108/ijopm-02-2014-0098
21. Barocas S, Nissenbaum H. Big data's end run around procedural privacy protections. Commun ACM, Nov 2014; 57(11):31-33. Doi: 10.1145/2668897
22. Li YJY. Data-driven supply chain management in the era of big data. J Bus Res. 2020; 117:454-461.
23. Fosso Wamba S, Akter S, Edwards A, Chopin G, Gnanzou D. How 'big data' can make big impact: Findings from a systematic review and a longitudinal case study. Int J Prod Econ, Jul 2015; 165:234-246. Doi: 10.1016/J.IJPE.2014.12.031
24. Burkell JA. Remembering me: Big data, individual identity, and the psychological necessity of forgetting. Ethics Inf Technol, Mar 2016; 18(1):17-23. Doi: 10.1007/S10676-016-9393-1
25. Shah SA, Seker DZ, Hameed S, Draheim D. The rising role of big data analytics and IoT in disaster management: Recent advances, taxonomy and prospects. IEEE Access. 2019; 7:54595-54614. Doi: 10.1109/ACCESS.2019.2913340
26. Agbehadji IE, Awuzie BO, Ngowi AB, Millham RC. Review of big data analytics, artificial intelligence and nature-inspired computing models towards accurate detection of COVID-19 pandemic cases and contact tracing. Int J Environ Res Public Health, Aug 2020; 17(15):1-16. Doi: 10.3390/IJERPH17155330
27. Waller MA, Fawcett SE. Data science, predictive analytics, and big data: A revolution that will transform supply chain design and management. Journal of Business Logistics. 2013; 34(2):77-84. Doi: 10.1111/JBL.12010
28. Witkowski K. Internet of Things, Big Data, Industry 4.0 - Innovative Solutions in Logistics and Supply Chains Management. Procedia Eng. 2017; 182:763-769. Doi: 10.1016/j.proeng.2017.03.197
29. Chen H, Chiang RHL, Storey VC. Business intelligence and analytics: From big data to big impact. MIS Q. 2012; 36(4):1165-1188. Doi: 10.2307/41703503
30. Fan J, Han F, Liu H. Challenges of Big Data analysis. Natl Sci Rev, Jun 2014; 1(2):293-314. Doi: 10.1093/NSR/NWT032
31. Price WN, Cohen IG. Privacy in the age of medical big data. Nat Med, Jan 2019; 25(1):37-43. Doi: 10.1038/S41591-018-0272-7
32. Chen YFYWL. Big data driven sustainable development of FMCG industry. J Clean Prod. 2020; 273.
33. Schroeder R. Big Data and the brave new world of social media research. Big Data Soc, Jul 2014; 1(2). Doi: 10.1177/2053951714563194
34. Murdoch TB, Detsky AS. The inevitable application of big data to health care. JAMA, Apr 2013; 309(13):1351-1352. Doi: 10.1001/JAMA.2013.393
35. Cate FH, Mayer-Schönberger V. Tomorrow's privacy: Notice and consent in a world of Big Data. International Data Privacy Law, May 2013; 3(2):67-73. Doi: 10.1093/IDPL/IPT005
36. Štufi M, Bačić B, Stoimenov L. Big data analytics and processing platform in Czech Republic healthcare. Applied Sciences (Switzerland), Mar 2020; 10(5). Doi: 10.3390/APP10051705
37. Tawalbeh L, Mehmood R, Benkhlifa E, Song H. Cloud Computing Model and Big Data Analysis for Healthcare Applications. IEEE Access. 2016; 4.
38. Baesens B, Bapna R, Marsden JR, Vanthienen J, Zhao JL. Transformational Issues of Big Data and Analytics in Networked Business. MIS Quarterly, Apr 2016; 40(4):807-818. Doi: 10.25300/MISQ/2016/40:4.03
39. Baesens B, Bapna R, Marsden JR, Vanthienen J, Zhao JL. Transformational issues of big data and analytics in networked business. MIS Quarterly, Dec 2016; 40(4):807-818. Doi: 10.25300/misq/2016/40:4.03
40. Cha HS, *et al*. The Korea cancer big data platform (K-CBP) for cancer research. Int J Environ Res Public Health, Jul 2019; 16(13). Doi: 10.3390/IJERPH16132290
41. Kruse CS, Goswamy R, Raval Y, Marawi S. Challenges and opportunities of big data in health care: A systematic review. JMIR Med Inform, Oct 2016; 4(4). Doi: 10.2196/MEDINFORM.5359
42. Wang W, Krishnan E. Big data and clinicians: A review on the state of the science. JMIR Med Inform, Jan 2014; 2(1). Doi: 10.2196/MEDINFORM.2913
43. See-To EWK, Ngai EWT. Customer reviews for demand distribution and sales nowcasting: A big data approach. Ann Oper Res, Nov 2018; 270(1-2):415-431. Doi: 10.1007/S10479-016-2296-Z
44. Moses JCLB. Using big data for legal and law enforcement decisions: Testing the new tools. Univ. New South Wales Law J. 2014; 37(2):643-678.

45. Song M, Du Q, Zhu Q. A theoretical method of environmental performance evaluation in the context of big data. Production Planning and Control. 2017; 28(11-12):976-984. Doi: 10.1080/09537287.2017.1336801
46. Fargnoli M, Haber N. Big data analytics in supply chain management: A comprehensive review and future research directions. Comput Ind Eng, Jan 2019; 128:851-863. Doi: 10.1016/j.cie.2018.10.042
47. Zhang YHGXH. Big data analytics for fast-moving consumer goods supply chain management: A review. J Ind Inf Integr. 2018; 9:52-60.
48. Zhao R, Liu Y, Zhang N, Huang T. An optimization model for green supply chain management by using a big data analytic approach. J Clean Prod, Jan 2017; 142:1085-1097. Doi: 10.1016/j.jclepro.2016.03.006
49. Wang G, Gunasekaran A, Ngai EWT, Papadopoulos T. Big data analytics in logistics and supply chain management: Certain investigations for research and applications. Int J Prod Econ, Jun 2016; 176:98-110. Doi: 10.1016/j.ijpe.2016.03.014
50. Raguseo E, Vitari C. Investments in big data analytics and firm performance: An empirical investigation of direct and mediating effects. Int J Prod Res, Aug 2018; 56(15):5206-5221. Doi: 10.1080/00207543.2018.1427900
51. Zhong RY, Newman ST, Huang GQ, Lan S. Big Data for supply chain management in the service and manufacturing sectors: Challenges, opportunities, and future perspectives. Comput Ind Eng, Nov 2016; 101:572-591. Doi: 10.1016/j.cie.2016.07.013
52. Big data analytics in logistics and supply chain management: Certain investigations for research and applications - ScienceDirect. Accessed: Jul 3, 2019 [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0925527316300056
53. Baccarelli E, Cordeschi N, Mei A, Panella M, Shojafar M, Stefa J. Energy-efficient dynamic traffic offloading and reconfiguration of networked data centers for big data stream mobile computing: Review, challenges, and a case study. IEEE Netw, 2016.
54. Belaud JP, Negny S, Dupros F, Michéa D, Vautrin B. Collaborative simulation and scientific big data analysis: Illustration for sustainability in natural hazards management and chemical process engineering. Comput Ind. 2014; 65(3):521-535. Doi: 10.1016/j.compind.2014.01.009
55. Lin L, *et al*. Development and implementation of a dynamically updated big data intelligence platform from electronic health records for nasopharyngeal carcinoma research. British Journal of Radiology. 2019; 92(1102). Doi: 10.1259/BJR.20190255
56. Quality Assessment. Encyclopedia of Big Data Technologies, 2019, 1325-1325. Doi: 10.1007/978-3-319-77525-8_100271
57. Jiang W. An Intelligent Supply Chain Information Collaboration Model Based on Internet of Things and Big Data. IEEE Access. 2019; 7:58324-58335. Doi: 10.1109/ACCESS.2019.2913192
58. Zhang JWY. Data-driven modeling and scientific computing. Appl Mech Rev. 2016; 68(5):050801-051013.
59. Brunton JNKSL. Data-driven versus physics-based modeling. Annu Rev Fluid Mech. 2018; 50:645-668.
60. Kadlec P, Gabrys B, Strandt S. Data-driven Soft Sensors in the process industry. Comput Chem Eng, Apr 2009; 33(4):795-814. Doi: 10.1016/j.compchemeng.2008.12.012
61. Goodall P, Sharpe R, West A. A data-driven simulation to support remanufacturing operations. Comput Ind, Feb 2019; 105:48-60. Doi: 10.1016/J.COMPIND.2018.11.001
62. Kumar Jain P, Mandli K, Hoteit I, Knio O, Dawson C. Dynamically adaptive data-driven simulation of extreme hydrological flows. Ocean Model (Oxf), Feb 2018; 122:85-103. Doi: 10.1016/J.OCEMOD.2017.12.004
63. Lee YCHKJ. Data-driven approach for production planning optimization in semiconductor manufacturing. Comput Ind Eng. 2020; 141. Doi: 10.1016/j.cie.2019.106328
64. Guo XLJLJ. Physics-based and data-driven modeling: A comparative study. Mathematics. 2019; 7(3):607-623.
65. Song Y, Routray R, Jain R, Tan CH. A data-driven storage recommendation service for multitenant storage management environments. Proceedings of the 2015 IFIP/IEEE International Symposium on Integrated Network Management, IM 2015, Jun 2015, 1026-1040. Doi: 10.1109/INM.2015.7140429
66. Chen JLZZY. A novel data-driven approach for demand forecasting in FMCG supply chain. IEEE Access. 2019; 7:152678-152687.
67. Meng C, Nageshwaraniyer SS, Maghsoudi A, Son YJ, Dessureault S. Data-driven modeling and simulation framework for material handling systems in coal mines. Comput Ind Eng. 2013; 64(3):766-779. Doi: 10.1016/J.CIE.2012.12.017
68. Xu Z, Dang Y, Munro P, Wang Y. A data-driven approach for constructing the component-failure mode matrix for FMEA. J IntellManuf, Jan 2020; 31(1):249-265. Doi: 10.1007/s10845-019-01466-z
69. Wang J, Das S, Rai R, Zhou C. Data-driven simulation for fast prediction of pull-up process in bottom-up stereo-lithography. CAD Computer Aided Design, Jun 2018; 99:29-42. Doi: 10.1016/J.CAD.2018.02.002
70. Cavalcante IM, Frazzon EM, Forcellini FA, Ivanov D. A supervised machine learning approach to data-driven simulation of resilient supplier selection in digital manufacturing. Int J Inf Manage, Dec 2019; 49:86-97. Doi: 10.1016/J.IJINFOMGT.2019.03.004
71. Oruezabala G, Rico JC. The impact of sustainable public procurement on supplier management - The case of French public hospitals. Industrial Marketing Management, May 2012; 41(4):573-580. Doi: 10.1016/j.indmarman.2012.04.004
72. Meehan J, Bryde D. Sustainable procurement practice. Bus Strategy Environ, Feb 2011; 20(2):94-106. Doi: 10.1002/BSE.678
73. Mishra AN, Devaraj S, Vaidyanathan G. Capability hierarchy in electronic procurement and procurement process performance: An empirical analysis. Journal of Operations Management. 2013; 31(6):376-390. Doi: 10.1016/j.jom.2013.07.011
74. Passaris C. The Business of Globalization and the Globalization of Business. Journal of Comparative International Management. 2006; 9(1):3-18. Accessed: Sep. 15, 2019. [Online]. Available:

https://id.erudit.org/iderudit/jcim9_1art01
75. Acar AZ, Zehir C. The harmonized effects of generic strategies and business capabilities on business performance. Journal of Business Economics and Management. 2010; 11(4):689-711. Doi: 10.3846/JBEM.2010.34
76. Pang C, Wang Q, Li Y, Duan G. Integrative capability, business model innovation and performance: Contingent effect of business strategy. European Journal of Innovation Management, May 2019; 22(3):541-561. Doi: 10.1108/EJIM-09-2018-0208
77. Jaswal S. Integrating business intelligence with cloud computing. Impacts and Challenges of Cloud Business Intelligence, Dec 2020, 41-56. Doi: 10.4018/978-1-7998-5040-3.CH004
78. Chaudhuri S, Dayal U, Narasayya V. An overview of business intelligence technology. Commun ACM, Aug 2011; 54(8):88-98. Doi: 10.1145/1978542.1978562
79. Osho GO, Omisola JO, Shiyanbola JO. An Integrated AI-Power BI Model for Real-Time Supply Chain Visibility and Forecasting: A Data-Intelligence Approach to Operational Excellence. Unknown Journal, 2020.
80. Ghamizi S, *et al*. Data-driven Simulation and Optimization for Covid-19 Exit Strategies. Proceedings of the ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, Aug 2020, 3434-3442. Doi: 10.1145/3394486.3412863
81. Seyedan M, Mafakheri F. Predictive big data analytics for supply chain demand forecasting: Methods, applications, and research opportunities. Journal of Big Data, Jul 2020; 7(1):1-22. Doi: 10.1186/S40537-020-00329-2
82. Willetts M, Atkins AS, Stanier C. Barriers to SMEs Adoption of Big Data Analytics for Competitive Advantage. 4th International Conference on Intelligent Computing in Data Sciences, ICDS 2020, Oct 2020. Doi: 10.1109/ICDS50568.2020.9268687
83. Huang J, Wang H, Fan M, Zhuo A, Sun Y, Li Y. Understanding the Impact of the COVID-19 Pandemic on Transportation-related Behaviors with Human Mobility Data. Proceedings of the ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, Aug 2020, 3443-3450. Doi: 10.1145/3394486.3412856/SUPPL_FILE/3394486.3412856.MP4
84. Huang J, Wang H, Fan M, Zhuo A, Li Y. Personalized Prefix Embedding for POI Auto-Completion in the Search Engine of Baidu Maps. Proceedings of the ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, Aug 2020, 2677-2685. Doi: 10.1145/3394486.3403318
85. Bar-Sinai M, Sweeney L, Crosas M. DataTags, Data Handling Policy Spaces and the Tags Language. Proceedings - 2016 IEEE Symposium on Security and Privacy Workshops, SPW 2016, Aug 2016, 1-8. Doi: 10.1109/SPW.2016.11
86. Rossi A, Lenzini G. Transparency by design in data-informed research: A collection of information design patterns. Comput. Law Secur. Rev, Jul 2020; 37:p. 105402. Doi: 10.1016/j.clsr.2020.105402
87. Hemerly J. Public policy considerations for data-driven innovation. Computer (Long Beach Calif). 2013; 46(6):25-31. Doi: 10.1109/MC.2013.186
88. Park YR, *et al*. Utilization of a clinical trial management system for the whole clinical trial process as an integrated database: System development. J Med Internet Res, Apr 2018; 20(4). Doi: 10.2196/JMIR.9312
89. Geissbuhler A, *et al*. Trustworthy reuse of health data: A transnational perspective. Int J Med Inform, Jan 2013; 82(1):1-9. Doi: 10.1016/J.IJMEDINF.2012.11.003
90. Wang JLLTT. Data-driven fast moving consumer goods supply chain model and application. Int J Control Autom. 2018; 11(5):125-138.
91. Ioannidis JPA. Informed Consent, Big Data, and the Oxymoron of Research That is Not Research. American Journal of Bioethics, Apr 2013; 13(4):40-42. Doi: 10.1080/15265161.2013.768864
92. Martin RF, Parisi DR. Data-driven simulation of pedestrian collision avoidance with a nonparametric neural network. Neurocomputing, Feb 2020; 379:130-140. Doi: 10.1016/J.NEUCOM.2019.10.062
93. Mittelstadt BD, Floridi L. The Ethics of Big Data: Current and Foreseeable Issues in Biomedical Contexts. Sci Eng Ethics, Apr 2016; 22(2):303-341. Doi: 10.1007/S11948-015-9652-2
94. Kaushik A, Raman A. The new data-driven enterprise architecture for e-healthcare: Lessons from the indian public sector. Gov Inf Q. 2015; 32(1):63-74. Doi: 10.1016/J.GIQ.2014.11.002
95. Mackey TK, *et al*. Big data, natural language processing, and deep learning to detect and characterize illicit COVID-19 product sales: Infoveillance study on Twitter and Instagram. JMIR Public Health Surveill, Jul 2020; 6(3). Doi: 10.2196/20794
96. Rosenbaum S. Data governance and stewardship: Designing data stewardship entities and advancing data access. Health Serv Res, Oct 2010; 45(5), Part 2, 1442-1455. Doi: 10.1111/J.1475-6773.2010.01140.X
97. Donoho D. 50 Years of Data Science. Journal of Computational and Graphical Statistics, Oct 2017; 26(4):745-766. Doi: 10.1080/10618600.2017.1384734
98. Aswani A, Shen ZJM, Siddiq A. Inverse optimization with noisy data. Oper Res, May 2018; 66(3):870-892. Doi: 10.1287/OPRE.2017.1705
99. Boyne SM. Data Protection in the United States. American Journal of Comparative Law, Jul 2018; 66:299-343. Doi: 10.1093/AJCL/AVY016
100. Slokom M. Comparing recommender systems using synthetic data. RecSys 2018 - 12th ACM Conference on Recommender Systems, Sep 2018, 548-552. Doi: 10.1145/3240323.3240325
101. Flick U. Doing Qualitative Data Collection - Charting the Routes. The SAGE Handbook of Qualitative Data Collection, Jan 2018, 3-16. Doi: 10.4135/9781526416070.N1
102. Martin N, Matt C, Niebel C, Blind K. How Data Protection Regulation Affects Startup Innovation. Information Systems Frontiers, Dec 2019; 21(6):1307-1324. Doi: 10.1007/S10796-019-09974-2/FIGURES/2
103. Bowen CM, Liu F. Comparative study of differentially private data synthesis methods. Statistical Science, May 2020; 35(2):280-307. Doi: 10.1214/19-STS742