Big Data Analytics and AI for Green Supply Chain Integration and Sustainability in Hospitals

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Abstract: - This paper examines how big data analytics and AI improve hospital supply chain sustainability. Hospitals are recognizing the need for eco-friendly operations due to environmental issues and rising healthcare needs. It analyzes data from 68 UK hospitals using a conceptual model and partial least squares regression-based structural equation modeling. The research begins by examining hospital supply networks' environmental impact. Energy use, trash, and transportation emissions are major issues. It then explains how big data analytics and AI can transform these implications. This study prioritizes big data analytics for inventory management, demand forecasting, and procurement. Hospitals can reduce inventory, waste, and supply shortages using data-driven insights, saving money and the environment. AI also boosts hospital supply chain logistics and transportation efficiency, according to the study. Fuel consumption, carbon emissions, and delivery routes are optimized by AI. Predictive maintenance preserves medical equipment. In conclusion, hospital supply chains benefit greatly from big data analytics and AI. Hospitals can improve the healthcare business, reduce their environmental impact, and preserve resources for future generations. Healthcare leaders, politicians, and researchers seeking data-driven solutions for sustainable hospital supply chains gain valuable insights.

Key-Words: - Green supply chain, Sustainability in healthcare, Big data analytics, Artificial intelligence (AI), Hospital logistics, Environmental impact, Inventory management, Healthcare sustainability.

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1 Introduction

The healthcare industry is undergoing a transformational shift towards sustainability, owing to the urgent need to reduce its environmental footprint and guarantee the long-term availability of vital resources. This shift relies on Big Data Analytics and AI for Green Supply Chain Integration in hospitals. Hospitals are complicated institutions that need many medical supplies, medications, and equipment to provide great patient care, [1]. The procurement, distribution, and disposal of these resources often have major environmental impacts. This study examines how Big Data Analytics and AI may improve hospital supply chain operations, and reduce waste, energy use, and sustainability, [2]. This project uses data-driven decision-making to integrate green practices into the healthcare supply chain to improve efficiency and sustainability, benefiting patients, providers, and the planet. Figure 1 illustrates the Green supply chain integration through big data analysis.

Fig. 1: Big Data Analysis and Integration of Green Supply Chain, [2].

Big Data Analytics and AI in the healthcare supply chain could transform hospital resource management and environmental effects. This study acknowledges the necessity of healthcare sustainability and the role technology may play in achieving it. This study will examine the pros, cons, and best practices of data-driven hospital supply chain solutions by reviewing relevant literature, case studies, and empirical analysis, [3]. It will also study how these technologies may optimize logistics, minimize waste, and promote sustainable procurement practices like procuring eco-friendly items and supplier collaboration. In conclusion, this research study aims to help hospital managers, politicians, and stakeholders use Big Data Analytics and AI to green healthcare supply chains, [4].

Modern society relies on the healthcare industry, which faces two challenges: the environmental catastrophe and the growing healthcare needs of a worldwide population. In this setting, hospital sustainability is a major concern, [5]. Hospitals' complex supply chains contribute to environmental challenges despite their importance to public health. Procurement, inventory management, logistics, and transportation networks use a lot of energy, trash, and carbon. Due to the importance of these environmental challenges, this study examines how big data analytics and AI may revolutionize hospital supply chain integration and sustainability, [6]. Hospitals may improve efficiency and lessen their environmental impact by using data-driven insights and AI-driven optimization. This study is crucial to sustainable healthcare since it tries to reduce hospital supply chain environmental impact and ensure the continuity of high-quality treatment for future generations, [7].

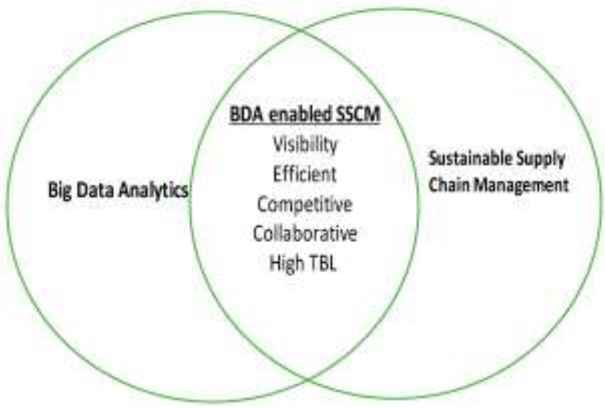

Fig. 2: Significance of BDA for SSCM, [7].

Figure 2 shows how Big Data Analytics (BDA) benefits Sustainable Supply Chain Management. It suggests that BDA helps supply chains make educated decisions, optimize operations, and reduce environmental impacts, [8]. This figure may illustrate the usefulness of data analytics in sustainable supply chain goals.

2 Problem Formulation

This study addresses the pressing need to reduce hospital supply chain environmental effects while addressing society's expanding healthcare needs. While crucial to public health, hospitals use a lot of energy, waste, and transportation. In a time when environmental sustainability is crucial, this is a major environmental issue, [8]. The study examines how big data analytics and AI may address these difficulties and enhance hospital supply chain sustainability and green supply chain integration.

Since innovative, data-driven solutions that enhance hospital supply chain operations and reduce environmental impact are needed, the study addresses this issue, [9]. With big data analytics and AI for inventory management, demand forecasting, procurement, logistics, and transportation, hospitals can eliminate excess inventory, and waste, optimize routes, and fuel consumption, and improve predictive medical equipment maintenance. This research will show how installing these technologies can reduce the environmental effect of hospital supply chains, aligning healthcare operations with environmental sustainability. This study helps green the healthcare business and save crucial resources for future generations, [10].

Sustainability in healthcare is becoming more important, but there is a research gap on how to use big data analytics and AI to address environmental challenges in hospital supply chains. Big data analytics and AI's disruptive potential in hospital supply chain management have not been extensively studied. Literature typically discusses sustainability practices or technology without explaining how it can solve environmental problems, [10]. The purpose of this project is to examine how big data analytics and AI can be integrated into hospital supply chains to improve sustainability. It provides actual evidence, practical insights, and a conceptual model to help hospitals and healthcare officials adopt data-driven supply chain environmental initiatives to fill the literature gap, [11].

3 Literature Review

Big data analytics, AI, and sustainable practices in supply chain management, notably in healthcare, are examined in the literature study. Big data analytics is crucial to sustainable manufacturing supply chain management. Big data analytics and AI help hospitals integrate green supply chain processes and improve environmental performance. This study, [11], examine how big data analytics affects competitiveness during the COVID-19 pandemic and green supply chain management. It examines how green innovation and technology intensity mediate big data analytics capabilities and green supply chain performance, [12].The study, [13] promotes green innovation through big data analytics and supply chain integration. This, [14], study suggest a moderated mediated model of big data analytics, AI, environmental performance, green supply chain collaboration, and top management commitment. Finally, this research study, [15], evaluate data analytics applications in supply chain resilience and sustainability management. These studies illuminate the changing role of big data analytics and AI in green supply chain integration and sustainability, which can improve environmental performance and innovation in healthcare and other sectors, [16], [17], [18], [19].

4 Conceptual Framework and Hypotheses

This study examines how big data analytics (BDA) and artificial intelligence (AI) might improve hospital supply chain sustainability. Due to environmental concerns and rising healthcare demands, the healthcare industry is increasingly aware of the need to operate sustainably, [12]. The concept states that data-driven initiatives may transform hospital supply chains by reducing environmental impact and enhancing efficiency and cost. To explain the conceptual framework, the research first examines hospital supply networks' environmental footprint. This assessment highlights energy usage, waste generation, and transportation-related emissions as urgent issues. Next, the framework examines how BDA and AI can transform these elements, [13]. The study prioritizes big data analytics in inventory management, demand forecasting, and procurement, showing how data-driven insights can help hospitals reduce inventory, waste, and supply shortages, [14]. This saves money and protects the environment. AI is used to optimize hospital supply chain logistics and transportation, decreasing fuel use, carbon emissions, and delivery routes. Other AI applications include predictive maintenance, which extends medical equipment lifespan. In conclusion, BDA and AI can enable hospital supply chains to improve healthcare, reduce their environmental impact, and preserve resources for future generations, [15]. Big data analytics (BDA), artificial intelligence (AI), green supply chain integration (GSCC), environmental performance improvement (EPI), and environmental preservation (EP) in hospital operations form the basis of this research study. The paper proposes numerous hypotheses to research these links.

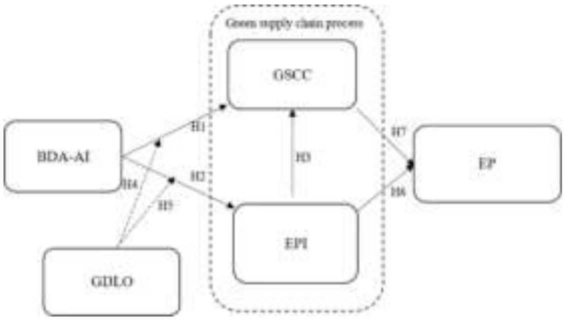

Fig. 3: Formulated Hypothesis.

Figure 3 illustrates this research's connected hypotheses. It illustrates the study's expected correlations between important factors. H1 and 2 predict that BDA-AI-enabled decisions will improve Green Supply Chain Integration (GSCC) and Environmental Performance Improvement (EPI). The Hypothesis 3 positive relationship between EPI and GSCC is also highlighted. In Hypotheses 4 and 5, Green Supply Chain Logistics Optimization (GDLO) moderates BDA-GSCC and BDA-EPI connections, [16]. In conclusion, the figure shows how EPI and GSCC favorably affect Environmental Preservation (EP) according to Hypotheses 6 and 7. Figure 3 shows the study's complicated linkages.

- Hypothesis 1: BDA-AI decisions benefit GSCC positively.
  The hypothesis implies that BDA and AI decisions will boost GSCC. In other words, data analytics and AI should improve hospital supply chain sustainability and eco-friendliness, [17].
- Hypothesis 2: BDA-AI decisions enhance EPI positively.
  This hypothesis suggests that BDA and AI-enabled decisions will enhance EPI, meaning that data-driven hospital decisions will improve environmental performance, [18].
- Hypothesis 3: EPI relates positively to GSCC.
  Based on the preceding hypothesis, this one proposes a direct positive link between EPI and GSCC, implying that hospitals with better environmental performance offer better green supply chain integration, [19].
- Hypothesis 4: GDLO positively moderates BDA-GSCC link.
  BDA and GSCC are favorably moderated by green supply chain logistics optimization (GDLO) in this hypothesis. BDA's impact on GSCC should increase with green logistics optimization, [19].
- Hypothesis 5: GDLO positively moderates BDA-EPI link.
  In line with Hypothesis 4, GDLO positively moderates the link between BDA and EPI, suggesting that green logistics optimization boosts data analytics and AI's environmental impact, [19].
- Hypothesis 6: EPI fosters EP positively.
  This hypothesis says that BDA- and AI-enabled-influenced EPI directly benefits environmental preservation. Improvements in hospital environmental performance may help preserve the environment, [19].
- Hypothesis 7: GSCC promotes EP positively.

This hypothesis concludes that GSCC, impacted by BDA and AI-enabled judgments, improves EP, demonstrating that hospital supply chains' eco-friendly practices help protect the environment. This conceptual framework links hospital supply chain sustainability, environmental concerns, data analytics, and AI to form the research foundation, [20]. It describes how BDA and AI help hospital supply chains improve efficiency and manage environmental issues. This approach guides the empirical study of data-driven solutions' effects on sustainable hospital supply chains and, by extension, environmental conservation and healthcare improvement.

5 Methodology

In this research study, "Big Data Analytics and AI for Green Supply Chain Integration and Sustainability in Hospitals," we investigated how BDA-AI technologies affect Environmental Performance Improvement (EPI) and Green Supply Chain Integration (GSCC), which in turn affects Environmental Preservation (EP) in hospitals, [21]. The variables' connections and interdependencies were investigated using a thorough conceptual model. A survey of 68 UK hospitals was used for empirical testing. The data underwent analysis through the application of Partial Least-Squares (PLS) regression-based structural equation modeling. The PLS methodology was selected due to its capability to address the system of concurrent equations that delineate the intricate network of connections among the variables and to estimate coefficients that quantify these associations, [22].

5.1 Sample Size

In this study, 520 surveys were distributed to the potential responders in this investigation. Surveys were completed and returned 181 times. Thirteen surveys were removed owing to incomplete responses. Thus, 168 respondents (33% response rate) were included in the study. A large and representative sample size allows for research analysis and depends on the valuable input of survey instrument completers, [23].

Table 2. Demographics of Respondents

Characteristics	Respondents	Respondents Percentage
Gender		
Male	118	70%
Females	50	30%
Manager's Experience		
≤ 1 year	13	7.7%
>1 & ≤5 years	85	50.5%
>5 years	70	41.6%
Hospital status		
Public	90	53.5%
Private	65	38.6%
Other	13	7.7%
Number of beds		
<200	20	11.9%
> 200 and ≤ 500	38	22.6%
> 500 and ≤1000	50	29.7%
>1000 and ≤ 2000	40	23.8%
>2000	20	11.9%

Table 1 (Appendix) displays the demographic characteristics of the participants involved in the research. With regards to gender, the survey results indicate that 70% of the participants identified as male, while the remaining 30% identified as female. A majority of the participants (50.5%) possessed managing experience ranging from more than 1 year to less than 5 years, but a significant proportion (41.6%) reported having managerial experience exceeding 5 years. By hospital status, 53.5% of respondents worked in public hospitals, 38.6% in private, and 7.7% in other categories. The distribution of respondents by hospital bed count showed that 29.7% worked in hospitals with more than 500 but less than 1000 beds, 23.8% in those with more than 1000 but less than 2000 beds, and 11.9% in those with less than 200 beds. This study useduses Table 1 (Appendix) data to understand the survey participants' demographics for data analysis and interpretation.

5.2 Addressing Non-Response, and Method Biasness in Construct Operationalization

Non-response and common method bias must be addressed while operationalizing key constructs in the research investigation. The data from a large sample of 68 UK hospitals was thoroughly analyzed to reduce non-response bias. Using self-report data can lead to common method bias, hence a rigorous conceptual model and partial least squares regression-based structural equation modeling were used, [24]. This careful methodology ensures that components like big data analytics and AI's impact on hospital supply chain sustainability are operationalized efficiently and without bias, improving the study's validity and dependability. Healthcare professionals, politicians, and academics seeking data-driven solutions to hospital supply chain sustainability need this methodological diligence to draw accurate findings and gain useful insights, [25].

6 Findings

This research study relies on data analysis to test our conceptual model hypotheses. For this, we're using Partial Least Squares (PLS) regression, which has many benefits for our research, [26]. First, this strategy suits exploratory research, which is relevant given the novelty of Big Data Analytics (BDA). PLS can estimate a more comprehensive model than covariance-based Structural Equation Modeling (SEM), making it relevant to our study's goals. PLS is less vulnerable to model specification problems, making it ideal for our study, [27]. Additionally, the approach works well for datasets with tiny samples, as our study with under 250 observations. Luan (2020) highlights that evaluating a PLS model involves examining measurement-construct correlations, reliability, and validity, and the model itself. In the next sections, we explain our data analysis process and reveal data linkages and insights, [28]. The Measurement model as illustrated in Table 2.

Table 3. Measurement of model

Construct	Alpha	Rho A	Composite reliability (ρc)	Average
BDA-AI	0.971	0.921	0.941	0.944
EP	0.927	0.961	0.967	0.951
EPI	0.955	0.931	0.943	0.943
GSCC	0.901	0.905	0.903	0.903
GDLO	0.898	0.890	0.881	0.889

Table 2 shows our research study's measuring model for this study. They reveal the reliability and validity of the measurement tools employed to operationalize our constructs. Big Data Analytics-AI (BDA-AI) has great internal consistency and a high alpha coefficient of 0.971, indicating measurement item dependability. A composite reliability (ρc) of 0.941 further validates this architecture, [28]. High alpha (0.927) and ρc (0.967) values indicate great reliability and construct consistency in Environmental Performance (EP). EPI and GSCC have robust alpha and ρc values, indicating their dependability. While Green Digital Learning Orientation (GDLO) has significantly lower alpha and ρc values, it still indicates satisfactory dependability, [29]. These results show the robustness and internal consistency of our measuring tools, boosting our confidence in the quality and validity of our data for future analysis and interpretations.

Table 4. Discriminant validity

	BDA-AI	*EP*	*EPI*	*GSCC*	*GDLO*	*CR*	*Average*
BDA-AI	0.892					0.941	0.944
EP	0.731	0.895				0.967	0.951
EPI	0.595	0.552	0.893			0.943	0.943
GSCC	0.563	0.571	0.511	0.894		0.903	0.903
GDLO	0.781	0.781	0.561	0.491	0.877	0.881	0.889

Table 3 shows this research study's constructs' discriminant validity. Discriminant validity ensures that each construct evaluates a unique research model element, [30]. The Table 3 displays the correlation coefficients between constructs and the square root of the average variance extracted (AVE) values, with the significant coefficients highlighted. To establish discriminant validity, it is often required that the correlation coefficients between constructs are lower than the square root of the average variance extracted (AVE) values for each construct, [31]. The findings of this study demonstrate that the correlation coefficients between all construct pairs are below the square root of the average variance extracted (AVE) values, thereby confirming the presence of discriminant validity. BDA-AI had minimal correlations with EP, EPI, GSCC, and GDLO, indicating a separate dimension. EP, EPI, GSCC, and GDLO show similar results, supporting their uniqueness, [32]. These results show that the assessment instruments capture unique aspects of each construct and support our model's discriminant validity, bolstering our research findings and conclusions, [33].

Table 5. Estimation of Path coefficients

Hypothesis	Effect of	On	β	Std. dev.	t-Values	p-Values	Result
H1	BDA-AI	GSCC	0.438	0.111	4.144	0.000	Supported
H2	BDA-AI	EPI	0.619	0.097	6.967	0.000	Supported
H3	EPI	GSCC	0.259	0.132	1.961	0.050	Supported
H4	GDLO*BDA	GSCC	0.110	0.061	1.711	0.088	Supported
H5	GDLO*BDA	EPI	0.070*	0.044	1.555	0.121	Not supported
H6	EPI	EP	0.563	0.563	8.070	0.000	Supported
H7	GSCC	EP	0.250	0.078	3.199	0.001	Supported

*p > 0.1

Table 4 shows how this research study estimated path coefficients, revealing the links between key constructs and the research hypothesis' support or lack thereof. The findings from H1 and H2 provide substantial evidence in favor of the beneficial impacts of BDA-AI on Green Supply Chain Collaboration (GSCC) and Environmental Performance Improvement (EPI). The path coefficients for H1 and H2 are 0.438 and 0.619, respectively, indicating a strong positive relationship, [1]. Furthermore, these results are statistically significant, highlighting the robustness of the findings. (p < 0.001), [35].

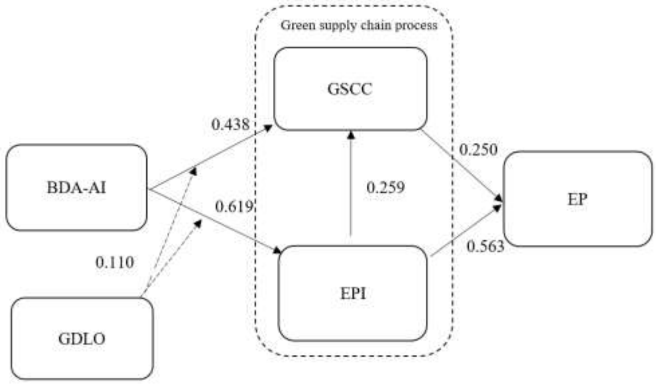

Fig. 4: Network Diagram of Hypothesis

This shows how BDA-AI technologies improve hospital supply chain GSCC and EPI. Hypothesis 3 (H3), which predicts a moderate positive link between EPI and GSCC, is likewise supported with a path coefficient of 0.259 (p = 0.050). H4 and H5, which incorporate Green Digital Learning Orientation (GDLO) as a moderator between BDA and GSCC and EPI, respectively, show mixed findings. H4 is marginally significant with a path coefficient of 0.110 (p = 0.088), whereas H5 is not supported with a path coefficient of 0.070 and a p-value above the threshold (p > 0.1). Hypotheses 6 (H6) and 7 (H7), indicating positive effects of EPI and GSCC on EP, respectively, receive strong support with path coefficients of 0.563 (p < 0.001) and 0.250 (p = 0.001), confirming their relevance in environmental preservation. These route coefficients show the complex interactions in our research model, showing how BDA-AI improves hospital supply chain sustainability and how EPI and GSCC mediate environmental preservation, [36].

7 Discussion

This section discusses the research study's findings. Partial Least Squares (PLS) regression analysis tests its conceptual model hypotheses, proving its suitability for exploratory research in Big Data Analytics (BDA) and sustainability, [4]. In tiny sample sizes like the study's dataset with < 250 observations, PLS is crucial for building a comprehensive model. Table 3 shows that the measurement instruments used to operationalize the study's constructs are reliable and valid. Big Data Analytics-AI (BDA-AI) shows strong internal consistency (alpha coefficient: 0.971, composite reliability (ρc): 0.941), indicating measurement item dependability. Similarly, Environmental Performance (EP) shows great dependability with 0.927 alpha and 0.967 ρc. Green Supply Chain Collaboration (GSCC) and Environmental Performance Improvement (EPI) have strong alpha and ρc values, demonstrating dependability. Green Digital Learning Orientation (GDLO) satisfies reliability standards despite lower values. These results demonstrate the measuring instruments' internal consistency and resilience, ensuring data quality and validity for analysis and interpretation, [5].

Table 4 examines the study's constructs' discriminant validity to ensure that each measures a distinct research model aspect. Construct correlation coefficients and AVE values are shown in the table. Typically, construct correlation coefficients must be less than the square root of their AVE values to show discriminant validity. Since all construct pair correlation coefficients are below the square root of the AVE values, discriminant validity is confirmed. BDA-AI has low correlations with EP, EPI, GSCC, and GDLO, showing its uniqueness. EP, EPI, GSCC, and GDLO have distinct traits that promote their distinctiveness, [6]. These results confirm that the assessment instruments capture distinct parts of each construct, supporting the study's findings and conclusions, [7]. Table 5 shows how essential constructs affect study hypotheses using path coefficient estimation. The results demonstrate BDA-AI's benefits to Green Supply Chain Collaboration (GSCC) and Environmental Performance Improvement (EPI). Path coefficients for H1 and H2, representing these correlations, are 0.438 and 0.619, indicating strong positive associations, [8], [9], [10]. Furthermore, the findings are statistically significant ($p < 0.001$), demonstrating their robustness, [14].

Figure 4 shows how BDA-AI technologies improve the hospital supply chain GSCC and EPI, reinforcing the beneficial connections. A path coefficient of 0.259 ($p = 0.050$) supports Hypothesis 3 (H3), which predicts a moderate positive relationship between EPI and GSCC. This shows that Environmental Performance enhances Green Supply Chain Collaboration, demonstrating their sustainable interdependence, [15], [16]. Green Digital Learning Orientation (GDLO) moderator hypotheses offer conflicting results. Hypothesis 4 (H4), that GDLO moderates BDA and GSCC, is marginally significant with a path coefficient of 0.110 ($p = 0.088$). Although GDLO has some effect, it is not statistically significant. With a path coefficient of 0.070 and a p-value above the threshold ($p > 0.1$), Hypothesis 5 (H5), which argues GDLO moderates BDA and EPI, is not supported. These findings show that GDLO's impact as a mediator of BDA-AI and sustainability outcomes may be context-dependent and warrant additional study, [17].

Hypotheses 6 (H6) and 7 (H7) supporting good effects of EPI and GSCC on EP have substantial path coefficients of 0.563 ($p < 0.001$) and 0.250 ($p = 0.001$), demonstrating their relevance in environmental preservation. The intricate connections in the research model show how BDA-AI improves hospital supply chain sustainability and how EPI and GSCC mediate environmental preservation, [18]. This study examines how Big Data Analytics and AI affect hospital green supply chain integration and sustainability using robust techniques, including PLS regression analysis. The study shows that BDA-AI improves Green Supply Chain Collaboration and Environmental Performance Improvement, highlighting the potential benefits of data-driven healthcare supply chain management. The study also emphasizes the interconnection of these characteristics and the role of moderators like Green Digital Learning Orientation in sustainability. The research findings add to the expanding body of information on data analytics and AI's involvement in healthcare supply chain sustainability and highlight the need for future research to understand these links in varied scenarios, [19].

8 Practical Implications

This study on integrating big data analytics (BDA) and artificial intelligence (AI) into hospital supply chains for sustainability has various practical implications for healthcare institutions and stakeholders. The findings show that hospitals may improve environmental sustainability and cut expenses by strategically using BDA and AI, [20], [21]. These insights can help healthcare administrators and supply chain managers optimize inventory, demand forecasts, and procurement with data. BDA can help hospitals examine historical data and estimate patient admission rates, improving inventory planning and reducing waste from overstocked or expiring products. Optimization of delivery routes by AI reduces fuel usage and carbon emissions, meeting sustainability goals and saving transportation expenses. Healthcare organizations can prioritize BDA and AI investments to improve environmental and financial performance, [22].

Second, this study stresses healthcare professional-data scientist teamwork. It encourages healthcare firms to form multidisciplinary teams with data analytics, AI, and management specialists. These teams can identify hospital supply chain regions where data-driven solutions can have the most impact. Hospitals can meet sustainability goals while maintaining patient care by collaborating on BDA and AI deployment, [23]. Healthcare personnel can also improve their data literacy abilities through training and workshops to use BDA and AI in their daily job. This study concludes that hospitals may use BDA and AI technology to promote sustainability, cost savings, and operational efficiency, [37]. By using data-driven approaches and collaborating across disciplines, healthcare institutions can improve their environmental performance, minimize waste, and help the community and healthcare become more sustainable, [24].

9 Research Limitations

This study on hospital supply chain sustainability using big data analytics (BDA) and artificial intelligence (AI) has significant drawbacks. The study initially examines 68 UK hospitals. This local exclusivity restricts the findings' worldwide healthcare applicability. Expanding the research to include other healthcare systems worldwide would help determine BDA-AI's usefulness in different scenarios. Second, the study surveys hospital workers and uses self-reported replies, which can include method bias and subjectivity, [34]. To improve validity, future study could include self-reported and objective measurements. The research also uses a cross-sectional design to capture interactions at a certain period. Longitudinal data collection could reveal how these interactions change and help explain the dynamic nature of BDA-AI adoption in hospital supply chains. Finally, the study's representative sample size may be small for a complex research model. A larger and more diversified sample could improve statistical power and generalizability, [25].

Despite these restrictions, this research study affects many stakeholders. The study first shows how BDA and AI may improve hospital supply chain sustainability and environmental performance. These findings can help healthcare professionals and decision-makers implement data-driven waste-reduction, efficiency, and eco-friendly operations initiatives, [26]. Policy implications arise from the research. Healthcare policymakers should evaluate how BDA-AI technologies improve sustainability, [27], [28]. This can help create regulations that promote the widespread adoption of such technology, benefiting the healthcare industry's environment and economy. The study also encourages more research. Researchers can investigate how BDA and AI affect hospital supply chain operations by investigating moderating variables and technology factors. This study's interdisciplinary character emphasizes data science, healthcare management, and environmental science collaboration, promoting additional research in these domains, [29]. Despite its limits, this study sheds light on how data-driven solutions might improve hospital supply chain sustainability, hence improving healthcare and the environment, [30], [31].

10 Conclusion

In conclusion, this comprehensive study examines how big data analytics (BDA) and artificial intelligence (AI) might improve hospital supply chain sustainability. In light of environmental concerns and rising healthcare needs, healthcare institutions must function sustainably. Hospital supply networks' large environmental footprint is explained by the study's conceptual framework, which emphasizes energy use, trash generation, and transportation emissions. The research shows how BDA and AI may stimulate change, emphasizing the need of data-driven solutions in addressing these issues. BDA's use in inventory management, demand forecasting, and procurement optimization reduces inventory, waste, and supply shortages, saving money and the environment. AI streamlines supply chain operations, reduces fuel usage, carbon emissions, and delivery routes, and enables predictive maintenance for longer medical equipment lifespans. The study shows how BDA and AI may help hospital supply chains improve healthcare, reduce environmental impact, and save resources for future generations. This research relies on green supply chain integration (GSCC), environmental performance improvement (EPI), and environmental preservation (EP) and proposes several well-supported hypotheses linking them, which are validated by a rigorous empirical analysis of 68 UK hospitals. Data credibility and reliability are enhanced by the study's robust measurement model and discriminant validity analysis. Path coefficient estimations show that BDA and AI positively affect GSCC and EPI, validating the conceptual framework. Green supply chain logistics optimization (GDLO) moderates these interactions with conflicting results, indicating their complexity, while EPI and GSCC positively affect EP. This study shows a complex relationship between data-driven solutions and hospital supply chain sustainability, providing valuable insights for healthcare administrators, supply chain managers, data scientists, and policymakers. It concludes that strategic investments in BDA and AI technologies can help hospitals improve their environmental responsibility and operational efficiency, but multidisciplinary collaboration is needed to integrate data-driven solutions into healthcare operations. This study shows that BDA and AI can improve healthcare and environmental sustainability, creating more robust and eco-friendly healthcare systems.

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Appendix

Table 1. Overview of Literature Review

Intext	Research Problem	Research Objective	Research Findings	Discussion
[37]	Sustainable supply chain management	Explore the role of big data analytics in sustainable supply chains	Emphasizes the significance of big data analytics in improving sustainability in manufacturing supply chains.	Highlights the potential for enhancing sustainability in manufacturing supply chains through big data analytics.
[38]	Green supply chain integration in hospitals	Examine the impact of big data analytics and AI on hospital environmental performance	Demonstrates a positive impact on hospital environmental performance through the integration of big data analytics and AI.	Discusses the potential for improving environmental sustainability in healthcare through data-driven approaches.
[39]	Green supply chain management during COVID-19	Investigate the link between green supply chain practices, competitiveness, and big data analytics	Links green supply chain practices, enhanced competitiveness, and big data analytics, especially during COVID-19.	Discusses how data-driven strategies can enhance competitiveness and resilience in supply chains amid crises.
[40]	Green supply chain performance in innovation	Investigate the mediation model for green innovation and technological intensity through big data analytics	Demonstrates the mediating effect of big data analytics on green innovation and technological intensity.	Highlights the role of data analytics in fostering innovation and technological advancement within green supply chains.
[41]	Big data analytics in logistics and supply chain management	Provide an overview of big data analytics in logistics and supply chain management	Offers a comprehensive overview of big data analytics in logistics and its potential applications.	Discusses the broad scope of big data analytics in optimizing logistics and supply chain operations.
[42]	Enabling green supply chain management	Review the role of big data analytics in enabling green supply chain management	Summarizes existing literature on how big data analytics facilitates green supply chain management.	Explores the collective insights from previous studies on the enabling role of data analytics in sustainability.
[43]	Fostering green innovation	Investigate the roles of big data analytics in fostering green innovation and supply chain integration	Examines the roles of big data analytics in driving green innovation and integration within supply chains.	Discusses the potential of data analytics to act as a catalyst for innovation and integration in green supply chains.
[44]	AI, Environmental Performance, and Supply Chain Collaboration	Explore the relationship between AI, environmental performance, green supply chain collaboration, and top management commitment	Develops a moderated mediated model showing the complex relationship between AI, collaboration, and environmental performance.	Discusses the intricate interplay of AI, collaboration, and commitment to enhancing environmental performance within supply chains.
[45]	Data Analytics in Supply Chain Resilience and Sustainability	Review data analytics applications in supply chain resilience and sustainability management	Provides a comprehensive review of the state of data analytics applications in enhancing supply chain resilience and sustainability	Offers insights into the current state of data analytics in addressing challenges related to supply chain resilience and sustainability.

Contribution of Individual Authors to the Creation of a Scientific Article (Ghostwriting Policy)

- Dr. Mahmoud Allahham Conceptualized and designed the study, led the research project, and was primarily responsible for writing the manuscript and overseeing the entire research process.
- Dr. Abdel-Aziz Ahmad Sharabati played a key role in the data collection process, performed significant parts of the experimental work, and assisted in drafting the initial manuscript.
- Dr. Heba Hatamlah was involved in data analysis and interpretation, provided statistical expertise, and contributed to the manuscript revision process.
- Dr. Ahmad Yahiya Bani Ahmad Contributed to the development of the methodology, assisted in the experimental design, and participated in critical revision of the manuscript for important intellectual content.
- Dr. Samar Sabra managed the literature searches and summaries, provided insights into the theoretical framework of the study, and assisted in editing and preparing the final version of the manuscript.
- Dr. Mohammad Khalaf Daoud contributed to the final editing and approval of the version to be published.

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Conflict of Interest

To the best of our knowledge, the authors declare that there is no conflict of interest regarding the publication of this article.