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Enhancing Humanitarian Supply Chain Resilience: Evaluating Artificial Intelligence and Big Data Analytics in Two Nations

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Abstract: *Background:* This study examines the application of Artificial Intelligence (AI) and Big Data Analytics (BDA) in enhancing humanitarian supply chain resilience, focusing on Ghana and South Africa. Despite their potential, AI-BDA applications are underexplored in disaster response, particularly in developing economies. *Methods:* An explanatory research design using a quantitative approach was employed, analyzing data from 200 supply chain professionals in both nations. Structured questionnaires assessed the implementation of four key AI-BDA techniques: Time-Series Forecasting (TSF), Early Warning Systems (EWS), Logistics Optimization (LO), and Real-time Monitoring (RTM). Exploratory factor analysis and regression analysis were conducted to evaluate the relationship between these techniques and supply chain resilience, controlling for organizational size and technological readiness. *Results:* The findings indicate that AI-BDA techniques significantly improve humanitarian supply chain resilience, with TSF and LO demonstrating the highest predictive power. Additionally, technological readiness facilitates the adoption of these techniques. *Conclusions:* While AI-BDA offers substantial benefits, opportunities for greater adoption remain, particularly in real-time monitoring and predictive analytics. Humanitarian organizations should invest in capacity-building initiatives, enhance data quality, and foster multi-stakeholder partnerships to maximize the impact of AI-BDA.

Keywords: artificial intelligence (AI); big data analytics (BDA); humanitarian supply chain resilience (HSCR); Ghana; South Africa

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1. Introduction

The humanitarian supply chains are responsible for delivering aid and essential resources to communities impacted by disasters, conflict, and other crises. However, these supply chains are characterised by unpredictable demand, logistical inefficiencies, and limited resources [1]. Over the past years, Artificial Intelligence (AI) and Big Data Analytics (BDA) have been recognised as a breakthrough approach that can advance Humanitarian Supply Chain Resilience (HSCR) by improving efficiency, decision-making, and adaptability in disaster response operations [2].

AI encompasses technologies such as machine learning, natural language processing, and computer vision, enabling predictive analytics and real-time decision-making in supply chain operations [3]. Similarly, BDA helps process and analyse vast amounts of structured and unstructured data to derive insights that improve supply chain responsiveness and operational efficiency [4]. In commercial supply chains, the synergy between Business Decision Analytics (BDA) and Artificial Intelligence (AI) has proven fruitful for inventory management, logistics, and demand forecasting.

Two of Africa's most renowned economies, Ghana and South Africa, frequently face recurring humanitarian challenges, including natural disasters, public health crises, and socio-political instability. Nonetheless, humanitarian organisations operating in these countries often face inefficient logistics, delayed response times, and resource misallocation, which further exacerbate the consequences of disasters on vulnerable populations [5]. Early Warning Systems (EWSs) driven by AI have proven effective in disaster prediction and resilience building [6]. Furthermore, humanitarian response efficiency can be significantly boosted through Logistics Optimisation (LO) and Real-Time Monitoring (RTM) as it streamlines the distribution and tracking of resources [7]. However, barriers, including data integration challenges, lack of technical expertise, and organisational resistance, prevent widespread AI-BDA adoption in humanitarian supply chains [8].

Empirical studies have demonstrated that the adoption of AI-BDA in humanitarian supply chains can increase visibility, optimise resource allocation, and improve coordination among humanitarian stakeholders [9]. For example, Zouari et al. [10] demonstrated that AI-powered supply chains lead to enhanced operational agility and responsiveness, resulting in reduced lead times and improved ability to respond to disruptions. Nevertheless, concerns about algorithmic bias, data privacy, and ethical issues remain pressing problems that need to be addressed to make responsible AI-BDA deployments feasible [11].

Despite their high potential for humanitarian use, the applications of AI and BDA are still limited and under-researched. In previous studies, Artificial Intelligence (AI) and Big Data Analytics (BDA) have been explored in the context of supply chain management, particularly in commercial logistics and industrial applications [9,12]. Moreover, a limited number of studies have investigated how AI and BDA are utilised to enhance supply chain resilience in humanitarian operations, primarily presenting theoretical frameworks and case-specific applications [2,7]. For instance, Dubey et al. [2] adopted the practice-based view as a theoretical framework to understand the impact of AI-BDA on HSCR. Still, they failed to account for the different AI-BDA techniques that affect HSCR. Abhulimen and Ejike [7] accounted for the different AI-BDA techniques. Still, their focus was on presenting a systematic review of studies and case examples, failing to present data-driven evidence to substantiate the integration of AI and BDA functions in humanitarian supply chains across multiple developing economies. While prior studies have indeed examined AI-BDA in supply chains, our research makes a unique contribution by empirically testing these relationships in the specific context of humanitarian operations in developing economies, disaggregating AI-BDA into distinct techniques to evaluate their comparative effectiveness, and providing data-driven evidence from a dual-national perspective that fills the knowledge gap between theoretical frameworks and practical implementation. The research questions below served as the main focus of this study's investigation:

RQ1: What are the existing AI-BDA techniques in humanitarian supply chains that enhance resilience in Ghana and South Africa?

RQ2: What are the effects of AI-BDA techniques in improving the resilience of humanitarian supply chains in Ghana and South Africa?

The findings from this research will impact practical applications, policy development, and future research in humanitarian operations. The research findings will offer practical evidence on how AI and BDA techniques can improve humanitarian operations while delivering specific implementation recommendations to optimise supply chain efficiency and impact. This study will provide policymakers with informed guidelines for implementing AI-BDA techniques in humanitarian organisations, particularly Ghana and South Africa. The insights gained from this research can support the development of policies that advance the effective deployment of digital tools in humanitarian work. Addressing the research gaps in the existing literature about AI-BDA applications within humanitarian

operations and the dissemination of findings in scholarly journal articles and conference presentations will expand opportunities for advanced research into AI-BDA applications within humanitarian operations. The research will support capacity building in humanitarian organisations by providing knowledge about effective techniques for handling modern supply chain management challenges during disaster response.

2. Literature Review

2.1. Theoretical Underpinnings

Three theoretical frameworks, namely, the Resource-Based View (RBV) Theory, Socio-Technical Systems (STSs) Theory, and Resilience Theory, were employed in the research to analyse the implementation of Artificial Intelligence—Big Data Analytics (AI-BDA) in humanitarian supply chains. These theories are crucial in justifying the hypotheses of this study and in understanding how the inclusion of AI-BDA mechanisms enhances supply chain resilience.

According to the Socio-Technical Systems (STSs) Theory [13], the effectiveness of organisations depends on the integration of social factors (people and processes) with technical factors (technology and tools). Eason [14] argues that optimal system performance results from the joint optimisation of the social and technical elements rather than treating them as separate entities. The STS Theory offers essential tools for navigating diversity and cultural complexity in dynamic humanitarian contexts [15]. Facilitating the analysis of the technological and social aspects of AI-BDA implementation enables the identification of potential barriers and integration issues. This is consistent with hypotheses suggesting that AI and BDA improve humanitarian supply chain resilience. According to the STS Theory, the successful adoption of AI-BDA requires a balanced approach that combines human expertise and technology, which is consistent with the idea that effective AI-BDA adoption should enhance operational efficiency and resilience in humanitarian supply chains.

According to the Resource-Based View (RBV) Theory, developed by Barney [16] following Wernerfelt [17], firms are strategically positioned through unique resources that are valuable, rare, inimitable, and non-substitutable. RBV enables humanitarian organisations to develop and maintain AI-BDA capabilities as a strategic asset. Rodríguez Espíndola et al. [18] applied RBV to understand how the capabilities of big data analytics contribute to increased operational efficiency and decision-making in humanitarian response. Based on the Resource-Based View (RBV) Theory, this study demonstrates how AI-BDA technologies can serve as strategic resources for enhancing supply chain resilience. It directly supports this hypothesis by evaluating whether AI-BDA can be considered a unique organisational capability for augmenting humanitarian operations. The study suggested that if AI-BDA is readily capitalised as a resource, it should facilitate supply chain agility and responsiveness, thereby validating the study's hypothesis.

The Resilience Theory [19] examines how systems respond to disruptions by maintaining their functionality due to their capacity for self-organisation and their ability to evolve [20]. According to Ponomarov and Holcomb [21], supply chain resilience comprises three core components: anticipation, adaptation, and recovery capabilities. By using the Resilience Theory as the basis for our study, we have a framework for examining how AI-BDA enhances the capacity of humanitarian organisations to anticipate, adapt to, and recover from disruptions. It directly supports the hypotheses because the theory explains how AI-BDA enables humanitarian supply chains to anticipate risks through predictive analytics, adapt to challenges through logistics optimisation, and recover from disruptions through real-time monitoring and early warning systems. The Resilience Theory, therefore, reinforces the study's hypothesis by highlighting how AI-BDA serves to enhance the robustness and flexibility of humanitarian supply chains.

Together, these theories provide an overarching understanding of how technology interacts with organisational resources to create system resilience in humanitarian supply chains. Their integration of STS Theory, RBV Theory, and Resilience Theory enables researchers to explore the impact of AI-BDA from technical, strategic, and adaptive dimensions, thereby justifying the study's hypothesis and contributing to the understanding of the effectiveness of AI-BDA in humanitarian operations [2].

2.2. Conceptual Review

2.2.1. Humanitarian Supply Chain Resilience (HSCR)

Humanitarian Supply Chain Resilience (HSCR) has become essential for disaster response and relief operations. The definition of HSCR includes the ability to protect against disruptions and ensure continuous operations through prevention, planning response, and mitigation [22]. The increasing frequency and complexity of disasters within challenging geopolitical contexts make HSCR essential for delivering life-saving humanitarian aid [23,24].

HSCR involves more than simple robustness or shock absorption capacity. Behl and Dutta [1] describe this as a dynamic ability that empowers humanitarian organisations to evolve through learning and development. Adaptability proves essential because humanitarian missions operate within unpredictable and changing environments, which became evident during the COVID-19 crisis [25].

The development of resilient humanitarian supply chains depends on several elements, such as pre-assessment [26], stakeholder engagement [27], strategic management [1], responsiveness [28], risk management [29], and material support [30]. The concept stresses the critical need for strategic planning, operational flexibility, and ongoing adjustments to dynamic conditions. L'Hermitte et al. [31] point out that sustainable strategic management needs to combine detailed strategic planning with flexible decision-making as disaster situations develop. By incorporating multiple elements into its strategy, humanitarian supply chains remain effective in handling different challenges and staying true to their primary purpose of assisting affected communities.

2.2.2. Existing Techniques of Artificial Intelligence and Big Data Analytics (AI-BDA) in Humanitarian Supply Chain Resilience (HSCR)

Time-Series Forecasting (TSF)

Time-Series Forecasting (TSF) has recently emerged as a critical application of Artificial Intelligence (AI) and Big Data Analytics (BDA), leveraging the prediction of future demand and disruptions to enhance humanitarian supply chain resilience. TSF enables proactive decision-making regarding resource allocation during crises [32,33]. Despite improved integration with advanced AI algorithms and machine learning techniques to enhance its predictive accuracy, its implementation is still constrained, and it has yet to realise its full potential in humanitarian operations.

A significant strength of TSF lies in addressing the inherent uncertainty of data, which is both pervasive and a fundamental issue in humanitarian operations. For instance, fuzzy time series analysis has been successfully applied to handle imprecise or incomplete data in emergencies [32]. Furthermore, case-based reasoning systems have aided organisations in forecasting by utilising past humanitarian responses and optimal resource allocation [33]. Nevertheless, these techniques are very dependent on having access to high-quality historical data, which is often absent in rapidly evolving disaster situations.

Furthermore, the integration of these SARIMA models [34] improved forecasting accuracy in medical supply chain management, taking into account both seasonal fluctuations and long-term trends. This is fundamental for humanitarian organisations that handle perishable goods, including vaccines and essential medicines. However, SARIMA

models become less effective as sudden and unexpected disruptions occur, such as new pandemics or significant, unexpected conflicts, as historical patterns are not a reliable guide to behaviour [35,36].

Recently, commodity-specific demand forecasting in humanitarian settings has been improved through the integration of robust principal component analysis and extended short-term memory networks [36]. The prediction capabilities of natural disasters using probability distribution-based tools also offer preparedness strategies [33]. Yet, these methods are very complex and require a significant amount of advanced computational infrastructure and specialised technical expertise, which many humanitarian organisations lack [9].

Deep learning algorithms, powered by the capabilities of TSF, work on massive volumes of real-time data to identify patterns and enable more predictable forecast generation. For instance, neural networks have been shown to surpass traditional statistical methods in predicting post-disaster resource needs [34]. However, deep learning models are still data-intensive and computationally demanding, which can present challenges in low-resource settings [35].

Moreover, recent modern TSF techniques utilise weather, population movements, and social media signals to make more refined predictions [36]. However, this multidimensional approach enhances adaptability in humans but at the cost of difficulties in data integration, privacy, and algorithm bias.

Early Warning Systems (EWSs)

Artificial Intelligence (AI) and Big Data Analytics (BDA) are developing Early Warning Systems (EWSs) that predict and prepare for disasters, serving as transformative tools in humanitarian supply chain management. From traditional monitoring tools to advanced predictive platforms, these systems have become proactive disaster response platforms and efficient resource allocation tools [6]. One of the strongest positive aspects of using AI-based EWS is their potential to increase the accuracy of disaster prediction. The accuracy rates of Machine Learning algorithms, such as Random Forest and Gradient Boosting, are very high, as studies have shown an accuracy rate of 86.7% in flood susceptibility prediction and 80% in flood risk classification [37]. They enable humanitarian organisations to preposition supplies and mobilise resources well in advance of disasters, providing greater responsiveness. While these models are effective, they rely upon the quality and quantity of historical data, which can be incomplete or inconsistent in resource-constrained areas [38].

EWS functionality has been further integrated with multi-source data, including satellite imagery, geological sensors, and social media [39]. By monitoring public response and detecting localised flooding, real-time social media data have also proven to be very effective [40]. These advancements enhance situational awareness, but they also raise concerns about data privacy, misinformation, and algorithmic biases that could lead to inappropriate predictions or the misallocation of resources [41].

Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks have significantly improved the accuracy and speed of deep learning techniques for disaster detection. In earthquake detection and flash flood prediction, these models have proved particularly promising [42,43]. Despite their general utility, they suffer from high computational power requirements and large amounts of training data, which limit their use by humanitarian organisations working in low-resource environments [44]. Moreover, they are black boxes, raising concerns about interpretability and accountability in decision-making [45].

EWS capabilities have been further strengthened by the seamless integration of Internet of Things (IoT) technologies, such as wireless sensor networks and cloud computing [46]. However, IoT-based EWS have also been shown to be an effective means of automating disaster alerts alongside improving coordination across relief agencies [47]. Challenges such as limited infrastructure, cybersecurity risks, and interoperability issues prevent their widespread adoption [48]. Modern EWS include predictive analytics to enhance supply chain resilience by forecasting risks and strategically allocating resources [49]. These systems improve logistical planning and reduce response times, but their effectiveness depends on overcoming technical, ethical, and infrastructural challenges.

Logistics Optimisation (LO)

Artificial Intelligence (AI) and Big Data Analytics (BDA) are relevant in the field of Logistics Optimisation (LO) to optimise humanitarian supply chains, contributing to operational efficiency in emergency response. With aid distributed post-disasters, artificial intelligence-driven optimisation techniques, such as multi-criteria decision-making models, vehicle routing algorithms, and digital twins, have transformed humanitarian logistics to increase delivery speed, resource allocation, and cost efficiency [7]. One of the significant benefits that AI-BDA brings to LO is its ability to address complex decision-making processes in dynamic environments. Humanitarian organisations can, with the use of multi-criteria decision-making models and heuristic algorithms, strike a balance among multiple operational goals, such as minimising response time, maximising resource coverage, and minimising cost efficiency [50]. In real-time route planning and last-mile delivery, these methods have been proven effective in disaster-stricken areas. Despite this, their performance depends on the availability and quality of the data, which can be unreliable in highly volatile humanitarian contexts [51].

Vehicle routing optimisation has been further improved through machine learning. For instance, RL models have surpassed traditional routing algorithms in complex emergency scenarios by dynamically adapting to changing conditions [52,53]. However, RL-based models are reliant on expensive computational resources and large datasets for training, which are often unfeasible for use in underdeveloped or disaster-prone areas [54].

Humanitarian logistics have benefited from the integration of mobile technology for real-time tracking and informed operational decision-making. The incorporation of mobile platforms facilitates the development of multi-objective decision-making models that optimise resource distribution, balancing economic and social factors [55]. Mobile-based LO offers good supply chain agility but suffers from poor network infrastructure, cybersecurity risk, and the lack of interoperability between humanitarian organisations [56].

With the emergence of digital twins comes a revolution in logistics, as they simulate logistics scenarios and enable proactive decision-making. By combining IoT, cloud computing, and AI-driven simulations, digital twins can help improve logistics coordination and risk assessment [57]. These systems enable real-time monitoring and predictive analysis of humanitarian operations. Digital twins are computationally intensive and require high-quality, real-time data inputs, making them undesirable in resource-constrained settings [58,59].

Real-Time Monitoring (RTM)

Real-Time Monitoring (RTM) has become a critical component of Artificial Intelligence (AI) and Big Data Analytics (BDA) applications in humanitarian supply chains, allowing organisations to track resources and respond swiftly to dynamic conditions. AI-powered monitoring systems improve responsiveness in unstable environments by providing continuous visibility into stock levels, resource movement, and potential supply

chain disruptions [7,60]. One of the most significant contributions of RTM is its ability to enhance logistical efficiency in disaster response. Sophisticated logistics management monitoring systems address critical challenges such as data collection, control mechanisms, and information display in remote and volatile environments [61]. These systems provide real-time visibility into relief goods, personnel, and medical supplies, enabling more effective coordination and resource allocation [62]. However, the reliability of RTM systems is highly dependent on network connectivity, which remains a major issue in disaster-prone and conflict-affected regions [63].

Integrating dynamic in-field data through technologies such as RFID and Wi-Fi has significantly improved location-tracking accuracy in humanitarian crises [64]. These technologies are especially valuable in emergency settings where traditional tracking methods may fail due to environmental hazards or infrastructure damage. However, their effectiveness is limited by technical constraints such as signal interference, high deployment costs, and the need for skilled personnel to manage and interpret data effectively [65].

Recent advancements in IoT sensors and edge computing have further strengthened RTM capabilities by enabling efficient data collection, processing, and analysis at the edge, reducing latency and improving decision-making speed in time-critical situations [66]. Smart container solutions equipped with environmental sensors have proven particularly useful in monitoring temperature-sensitive medical supplies [67,68]. Nonetheless, these innovations require significant investments in infrastructure, which may not be feasible for many humanitarian organisations operating in resource-constrained settings.

Blockchain technology has also emerged as a promising solution for enhancing data transparency and traceability in humanitarian supply chains [69]. By improving accountability, visibility, and trust, blockchain can mitigate issues related to fraud and inefficiencies in aid distribution [70]. However, the decentralised nature of blockchain raises concerns about data governance, interoperability, and the high computational costs associated with maintaining blockchain networks [71]. Additionally, AI-powered predictive analytics applied to RTM data can facilitate early detection of supply chain disruptions and automate response mechanisms [72,73]. While this enhances operational agility, predictive models can suffer from algorithmic biases and inaccuracies, leading to suboptimal decision-making in humanitarian contexts.

2.3. Empirical Evidence on the Effect of Artificial Intelligence and Big Data Analytics (AI-BDA) on Humanitarian Supply Chain Resilience (HSCR)

The existing literature highlights the significant role of Artificial Intelligence (AI) and Big Data Analytics (BDA) in enhancing supply chain resilience (SCR). Yet, discrepancies remain in their conceptualisation, methodological approaches, and reported outcomes. While some studies emphasise the contribution of AI-BDA to supply chain visibility and agility, others focus on its role in risk mitigation and strategic decision-making, highlighting inconsistencies in how AI-BDA is integrated into humanitarian supply chains.

Zouari et al. [10] explored the relationship between supply chain digitalisation and resilience, demonstrating that AI and BDA facilitate enhanced visibility across supply chain operations. Their study, using structural equation modelling (SEM) with 300 professionals, concluded that digital maturity and digital tools improve information flow and operational adaptability. Similarly, Belhadi et al. [34] expanded on this by identifying supply chain resilience (SCRes) and supply chain performance (SCP) as mediators between AI and dynamic supply chain environments. However, while both studies affirm the importance of digitalisation, Zouari et al. [10] focus on visibility as a primary driver. In contrast, Belhadi et al. [34] highlight performance metrics, suggesting a divergence in how the impact of AI-BDA is measured.

In contrast, Modgil et al. [74] adopted a qualitative approach, arguing that AI-BDA primarily enhances supply chain vulnerability management through five key drivers: transparency, last-mile delivery, customised supply chain solutions, disruption management, and flexible procurement. Their findings, based on interviews with 35 professionals, provide rich insights into the AI operational nuances but lack empirical validation through large-scale statistical analysis. This raises questions about the generalisability of their proposed framework compared to the SEM-based approaches of Zouari et al. [10] and Belhadi et al. [34].

Further complexity arises in Singh et al. [75] study, who employed Total Interpretive Structural Modelling (TISM) with 229 survey responses to develop a conceptual framework for AI-BDA adoption. Their results indicate that supply chain analytics plays a crucial role in resilience by improving demand forecasting and inventory management. However, their framework contrasts with Modgil et al. [74] by prioritizing data-driven adaptability over qualitative strategic drivers, suggesting potential inconsistencies in defining the AI role in resilience building.

A more sector-specific perspective is provided by Bag et al. [76], who investigated Big Data Analytics (BDA) in mitigating supply chain disruptions during the COVID-19 pandemic. Their study, based on automobile parts manufacturers in South Africa, used PLS-SEM to confirm that BDA contributes to restoring and increasing supply chain resilience. While their findings align with Zouari et al. [10] and Belhadi et al. [34] in highlighting the transformative role of AI-BDA, their sectoral focus limits the applicability of their conclusions to broader humanitarian supply chains.

Dubey et al. [2] offer another dimension by specifically assessing AI-driven BDA capabilities in humanitarian relief operations. Their survey of 171 international NGOs confirms that AI-BDA significantly enhances agility, resilience, and overall performance. However, in contrast to other studies focusing on commercial and industrial supply chains, their research contextualizes AI-BDA within humanitarian crises, reinforcing the necessity of real-time decision-making and operational flexibility.

These varying perspectives illustrate key contradictions in the literature: (1) whether the AI-BDA primary benefit lies in visibility [10] or performance enhancement [34]; (2) whether resilience is best achieved through strategic flexibility [74] or data-driven adaptability [75]; and (3) the extent to which sectoral applications influence the AI-BDA effectiveness [2,76]. The present study aims to reconcile these inconsistencies by adopting a dual-national perspective on AI-BDA adoption in humanitarian supply chains across Ghana and South Africa. Furthermore, it expands beyond commercial supply chains to examine context-specific applications in humanitarian logistics, addressing the contradictions in previous studies. It provides a more comprehensive understanding of the AI-BDA role in strengthening HSCR.

2.4. Hypothesis

Based on the empirical evidence, the following hypotheses are made:

H_{A1}: Time-Series Forecasting (TSF) will have a positive effect on humanitarian supply chain resilience.

H_{B1}: Early Warning Systems (EWSs) will have a positive effect on humanitarian supply chain resilience.

H_{C1}: Logistics Optimisation (LO) will have a positive effect on humanitarian supply chain resilience.

H_{D1}: Real-Time Monitoring (RTM) will have a positive effect on humanitarian supply chain resilience.

3. Materials and Methods

3.1. Research Design

The study employed an explanatory research design to examine the impact of AI-BDA applications on humanitarian supply chain resilience. This design is particularly appropriate as it enables the analysis of cause-and-effect relationships between AI-BDA implementation and supply chain resilience measures [77]. The approach aligns with the study's positivist paradigm, allowing for systematic testing of hypotheses and theoretical frameworks through statistical analysis [78].

The explanatory design facilitates examining how specific AI-BDA techniques affect different components of humanitarian supply chain resilience, including existing applications, their effectiveness, and implementation challenges [79]. This systematic approach enables the determination of relationship strength and direction between AI-BDA adoption and supply chain resilience outcomes [80]. Through statistical methods and quantitative analysis, the design supports evaluating AI-BDA applications' performance in enhancing supply chain resilience [81]. This approach generates evidence-based insights about the effectiveness of AI-BDA implementations in humanitarian operations, helping identify successful practices and areas that need improvement.

3.2. Study Population

The population for this study includes the supply chain management professionals directly involved in disaster response and relief in Ghana and South Africa. The selection of Ghana and South Africa as the focal countries is strategically justified by their contrasting yet complementary humanitarian and economic landscapes. Ghana, as a West African country, frequently experiences climate-related disasters such as floods and droughts, necessitating robust supply chain resilience strategies [82]. The country's evolving digital infrastructure and increasing adoption of AI-BDA make it a relevant context for examining the role of emerging technologies in disaster management [83]. In contrast, South Africa represents a more advanced economy with well-developed logistics networks but faces challenges related to political instability, infrastructure constraints, and natural disasters, including wildfires and droughts [84]. South Africa's established AI and data analytics ecosystem provides an opportunity to evaluate best practices in AI-BDA implementation within humanitarian logistics. The target population also includes supply chain managers, data scientists, IT specialists, and operational leaders who may be directly involved in deploying or managing AI-BDA systems in their organisations. Thus, the population selection in this study is quite general, which increases the possibility of obtaining a wide range of perceptions and practices across the humanitarian supply chain ecosystem.

3.3. Sampling Technique and Sample Size

The study employed a combination of purposive and convenience sampling to select participants with direct experience in implementing AI-BDA solutions in humanitarian supply chains. Purposive sampling was chosen to deliberately target professionals with expertise in AI-BDA applications within humanitarian operations. This ensured that the study obtained high-quality, relevant insights aligned with the research objectives [85]. Convenience sampling was also incorporated due to the challenge of accurately determining the total population of AI-BDA practitioners in humanitarian supply chains. Given the dynamic and often fragmented nature of humanitarian logistics, identifying a complete sampling frame proved difficult, making convenience sampling a practical approach to recruiting participants who were accessible and willing to participate.

The sample comprised 200 professionals from humanitarian organisations in Ghana and South Africa, including supply chain managers, data scientists, IT specialists, and

operational leaders. This sample size aligns with similar research in humanitarian supply chain resilience [9,86]. To enhance the reliability of the data, participants were required to have at least three years of experience in humanitarian supply chain management and direct involvement in AI-BDA projects. This criterion ensured that respondents possessed both technical and operational expertise relevant to the study [87].

While purposive and convenience sampling offer advantages in accessing knowledgeable participants, they also introduce potential selection bias and limited generalisability. Purposive sampling may lead to the overrepresentation of professionals with specific viewpoints. In contrast, convenience sampling could result in a sample that is not fully representative of the broader humanitarian supply chain community. To mitigate these biases, the study employed triangulation by sourcing respondents from multiple organisations, roles, and geographic locations within Ghana and South Africa. Additionally, efforts were made to include professionals from diverse humanitarian agencies, including international NGOs, government relief programs, and private sector logistics providers. By ensuring variation in organisational affiliation and role specialisation, the study enhanced the credibility and applicability of its findings within the humanitarian supply chain domain.

3.4. Data Collection Procedure

Primary data were collected through an online survey using Google Forms, chosen for its accessibility and user-friendly interface [88]. The questionnaire was structured to gather information about their demographics, existing AI-BDA techniques, and supply chain resilience implemented by their organisations.

The survey instrument utilised structured close-ended questions and Likert scales and underwent pre-testing with 30 field experts to ensure comprehension and accuracy [89]. The questionnaire was distributed to professionals in humanitarian organisations across Ghana and South Africa, including supply chain managers, data analysts, IT personnel, and operations managers.

Initial contact was established through professional networks and humanitarian organisation databases, followed by formal invitation emails containing survey information. Follow-up emails were sent bi-weekly over a three-month data collection period. Participant anonymity was maintained throughout the process [90]. Data were securely stored on a password-protected computer accessible only to the researcher, ensuring compliance with ethical research standards and data protection regulations.

3.5. Measures

Table 1 presents the measurement scales for the constructs used in the study.

Table 1. Measurement Scales for Constructs Used in the Study.

Construct	Item	Statement	Source
AI-BDA techniques in humanitarian supply chains	TSF1	Our organisation uses AI for demand prediction in humanitarian operations.	Adapted from Chan et al. [32] and Shah et al. [34].
	TSF2	We employ machine-learning algorithms for supply chain disruption forecasting.	
	TSF3	Our organisation utilises predictive analytics for medical inventory management.	
	EWS1	Our organisation employs machine learning for disaster risk prediction.	Adapted from Lamsal and Kumar [6] and Tomas et al. [37].
	EWS2	We use AI-powered systems for flood susceptibility prediction.	

Table 1. *Cont.*

Construct	Item	Statement	Source
	EWS3	Our early warning systems help pre-position supplies before disasters.	Adapted from Ortuño et al. [50], Serrato-Garcia et al. [56], and Abhulimen and Ejike [7].
	LO1	Our organisation uses AI algorithms to optimise delivery routes during crises.	
	LO2	We employ multi-objective optimisation models for resource allocation.	
	LO3	Our organisation uses AI for transportation network optimisation.	
	RTM1	Our organisation employs real-time tracking systems for supply visibility.	Adapted from Laguna Salvadó et al. [62], Yang et al. [63], and Budak et al. [65].
	RTM2	We use AI to monitor resource distribution in real-time.	
	RTM3	Our organisation utilises technology for real-time location tracking of humanitarian supplies.	
Humanitarian Supply Chain Resilience	HSCR1	We quickly restore the flow of items with the help of AI-BDA-driven technologies.	Adapted from Altay et al. [91] and Papadopoulos et al. [92].
	HSCR2	Information gathered using AI-BDA-driven technology helps us provide necessary relief materials during unexpected disruptions.	
	HSCR3	We maintain a buffer stock of essential relief items to tackle demand and supply uncertainties.	
	HSCR4	We quickly repair the damages caused to the basic property, schools, and other essential centres.	
Technology Readiness (TR)	TR1	AI and Big Data Analytics improve our ability to respond quickly to supply chain disruptions.	Adapted and modified from Parasuraman and Colby [93]
	TR2	The use of advanced technologies helps our organisation deliver aid more efficiently.	
	TR3	Our organisation is often among the first to adopt new digital tools for logistics operations.	
	TR4	I enjoy experimenting with emerging technologies that could improve humanitarian services.	
	TR5	I find it challenging to keep up with the complexity of AI and BDA tools used in our operations.	
	TR6	Sometimes, I feel overwhelmed by the amount of technical knowledge needed for AI-BDA systems.	
	TR7	I am concerned that AI-BDA systems might make critical errors in disaster response situations.	
	TR8	I worry that over-reliance on technology could reduce human judgment in decision-making.	
	TR9	Our organisation has the necessary infrastructure to support AI and BDA implementation.	
	TR10	Management is supportive of investing in AI and BDA to improve our humanitarian operations.	

3.6. Validity and Reliability

To enhance the reliability and validity of the research data, the following procedures were followed to confirm the research instrument's validity and reliability. Cronbach's Alpha coefficient was used to determine the internal consistency reliability of the data, and a coefficient above 0.7 was considered satisfactory for research [84,94]. The questionnaire's content validity was checked by experts in humanitarian supply chain management and artificial intelligence [95]. This expert review helped ensure that the measurement items captured the intended constructs and aligned with the objectives.

Construct validity was assessed based on both convergent and discriminant validity. Convergent validity was determined by using Average Variance Extracted (AVE), and the values should be above 0.5 for acceptable convergent validity [96,97]. Discriminant validity

was tested using the Fornell and Larcker [98] criterion by comparing the AVE square root with correlations between the construct and other constructs in the research model and ensuring that each construct differed from all other constructs [99,100]. However, the Fornell and Larcker [98] criterion fails to detect a lack of discriminant validity, especially when constructs are closely related; hence, an HTMT test was further conducted to determine the discriminant validity. According to Henseler et al. [101], the HTMT test is a more robust method to assess discriminant validity in variance-based structural equation modelling, outperforming the Fornell and Larcker criterion and cross-loadings in terms of reliability and power.

Furthermore, factor loadings for each item were also analysed to ensure that they met the minimum requirement of 0.7, as supported in the literature [99]. Exploratory Factor Analysis (EFA) is essentially a statistical technique used to uncover the underlying structure of a relatively large set of variables. The core purpose of EFA is to identify latent constructs or factors that explain the patterns of correlations among measured variables [100].

The face validity of the questionnaire was checked by modifying it several times according to the suggestion of the academic supervisor, who has experience in the humanitarian field [102]. The final instrument was also piloted for comprehension and simplicity to ensure the target respondents could effectively comprehend and properly answer the questions [103]. Such a systematic approach towards validating the measures ensured the reliability of the research instrument and the validity of the conclusions drawn from the research study.

3.7. Data Analysis

Concerning the research objectives, the data analysis process involved a comprehensive approach to ensure the objectives were met. Data cleaning and screening were carried out to check the quality of the data collected and to deal with the missing values using SPSS version 27.0. To meet the first research question that examined the existing AI-BDA techniques in humanitarian supply chains, the means and standard deviations were determined to analyse the techniques' application patterns. These analyses provided an understanding of the most frequent techniques applied in boosting supply chain resilience [104].

$$Mean,\ x = \frac{1}{n}\sum_{i=1}^{n} x_i \tag{1}$$

where,

n is the number of observations, and

x_i are the data values.

$$Standard\ deviation, \sigma = \sqrt{\frac{\sum_{i=1}^{n}(x_i - x)^2}{n}} \tag{2}$$

where,

n is the number of observations,

x_i are the data values, and

x is the mean

More importantly, the Exploratory Factor Analysis (EFA) was used to determine the factors that define AI-BDA techniques, with factors based on eigenvalues above 1 and factor loadings of 0.5 and above [105].

$$X = \Lambda F + \epsilon \tag{3}$$

X is the observed data matrix,

Λ is the loading matrix (factor loadings),
F is the factor matrix (latent variables), and
ϵ is the error matrix.

Inferential statistics were adopted to achieve the second objective, which focused on determining the effects of AI-BDA techniques on the resilience of the humanitarian supply chain. The study specifically adopted regression analysis, a potent analytical method to test the hypotheses (whether alternative or null hypotheses), thereby determining the relationship between the variables. The regression analysis also helped to determine the relative effects of the different AI-BDA techniques on HSCR.

3.8. Regression Model Specification

This research constructed a regression model to examine the relationship between the dependent (HSCR) and independent variables (AI-BDA, TSF, EWS, LO, RTM). Technology Readiness (TR) and Organization Size (OS) were included as confounding variables in the regression model. Technology Readiness (TR) reflects an organisation's capacity to adopt and utilise emerging technologies such as AI and BDA. Organisations with higher technological readiness are more likely to implement AI-BDA effectively, which, in turn, influences their supply chain resilience. Failing to account for this could bias the estimated effect of AI-BDA, attributing improvements in resilience to the technology alone rather than the organisation's preparedness to adopt it [105]. TR acts as an enabler and moderating factor that shapes both the likelihood and effectiveness of AI-BDA integration. Organisation Size (OS), typically measured by the number of employees, is another critical confounder. Larger organisations often have more resources—financial, technological, and human capital—that make AI-BDA implementation more feasible and effective [106]. They may also have more complex supply chains, making resilience-building efforts both more necessary and more impactful. Consequently, OS can influence both the decision to implement AI-BDA and the resulting outcomes in terms of HSCR, necessitating its inclusion to isolate the true effect of AI-BDA techniques.

By including TR and OS, the model controls for two structural attributes that may otherwise obscure the true relationship between AI-BDA and HSCR, enhancing the model's internal validity and reducing omitted variable bias [107]. Hence, the model specification for this study is as follows:

$$HSCR = a + \beta_1 TSF + \beta_2 EWS + \beta_3 LO + \beta_4 RTM + \beta_5 OS + \beta_6 TR + \varepsilon \quad (4)$$

where,

HSCR is Humanitarian Supply Chain Resilience,
TSF is Time-Series Forecasting,
EWS is Early Warning Systems,
LO is Logistics Optimisation,
RTM is Real-Time Monitoring,
OS is Organisation Size (measured by the number of employees in the organisation),
TR is Technology Readiness (measured using the adapted Technology Readiness Index (TRI 2.0) framework),
a is the intercept,
β1: β4 are coefficients, and
ε is the error term.

3.9. Ethical Considerations

The research adhered to comprehensive ethical guidelines to protect participant privacy and safety. Written informed consent was obtained from all participants after explain-

ing the study's purpose, potential effects, and benefits. Participants were informed of their right to withdraw from the study without consequences.

Strict confidentiality measures were implemented, with data access restricted to authorised personnel only. Contingency measures were established to support participants who might experience discomfort during the study, and cultural and diversity considerations were integrated into the data collection and analysis processes.

The study complied with Durban University of Technology's ethical procedures and international research standards. This included obtaining university ethical committee approval before data collection and ensuring ethical research design and procedures. Participants were fully informed about data usage and protection measures, maintaining transparency throughout the research process while preserving participant dignity and rights.

4. Results

This section presents the research findings and discusses them with the literature.

4.1. Demographic Information

The study participants represented diverse age groups, with the majority in the middle-to-upper age bracket (45–54 years: 21.5%, over 55: 21.5%), while younger demographics (under 25: 23.0%, 25–34: 22.0%, 35–44: 12.0%) provided balanced generational perspectives. Gender distribution showed slightly more female participants (57.5%) than males (42.5%). Educational backgrounds were varied, with professional certifications (16.5%), other qualifications (20.0%), secondary school (20.5%), master's degrees (14.5%), and doctorates (12.5%), indicating a highly skilled workforce. Professional roles were distributed among Operations Leaders (28.0%), IT Professionals (20.5%), Data Scientists (19.5%), and Supply Chain Managers (17.5%). Experience levels ranged from less than 3 years (36.0%) to 6–10 years (22.5%), with mid-range experience of 3–5 years (21.5%) and over 10 years (20.0%), reflecting a mixture of new talent and experienced professionals in the humanitarian sector.

4.2. Organisational Information

The study covered organisations across two African regions, with South Africa representing 29.0% of operations, Ghana 32.0%, and 39.0% operating in both countries.

The organisational types represented included International NGOs (24.0%), Local NGOs (20.5%), UN Agencies (21.0%), and Government Agencies (15.0%), with other types comprising 19.5%. Primary operational areas included Logistics and Transportation (24.0%), Disaster Response (18.0%), Warehouse Management (16.5%), Food Distribution (16.0%), and Medical Supply Chain (11.0%).

Experience with AI-BDA implementation revealed early adoption stages, with most organisations having less than three years of experience (28.0% less than one year, 25.0% having 1–3 years), 20.0% having 4–5 years, and 27% having more than 5 years of experience. This indicates that AI-BDA adoption in humanitarian supply chains is still emerging, with organisations at various implementation stages.

4.3. Artificial Intelligence and Big Data Analytics (AI-BDA) Techniques in Humanitarian Supply Chains

4.3.1. Descriptive Statistics

Table 2 explicitly illustrates the adoption levels of different AI-BDA techniques in humanitarian organisations, directly addressing our first research question about existing AI-BDA techniques in humanitarian supply chains. The highest mean scores are observed in EWS3 (4.09) and LO2 (3.95), suggesting that early warning systems for pre-positioning supplies and "employing multi-objective optimisation models for resource allocation" are

the most extensively implemented techniques. TS1 also shows relatively high adoption with a mean of 3.89. These scores, above the midpoint of 3.0, indicate above-average implementation levels.

Table 2. Descriptive statistics of HSCR techniques.

	Items	Mean	SD
TS1	Our organisation uses AI for demand prediction in humanitarian operations.	3.89	0.947
TS2	We employ machine-learning algorithms for supply chain disruption forecasting.	3.10	0.969
TS3	Our organisation utilises predictive analytics for medical inventory management.	3.00	1.005
EWS1	Our organisation employs machine learning for disaster risk prediction.	2.88	0.980
EWS2	We use AI-powered systems for flood susceptibility prediction.	2.77	1.000
EWS3	Our early warning systems help pre-position supplies before disasters.	4.09	0.858
LO1	Our organisation uses AI algorithms to optimise delivery routes during crises.	3.03	0.969
LO2	We employ multi-objective optimisation models for resource allocation.	3.95	0.950
LO3	Our organisation uses AI for transportation network optimisation.	2.84	1.018
RM1	Our organisation employs real-time tracking systems for supply visibility.	3.06	1.092
RM2	We use AI to monitor resource distribution in real-time.	2.96	1.048
RM3	Our organisation utilises technology for real-time location tracking of humanitarian supplies.	3.03	0.953

Conversely, several techniques show lower adoption levels, with EWS2 having the lowest mean (2.77), followed by LO3 (2.84) and EWS1 (2.88). Most other techniques cluster around means of 2.97–3.09, suggesting moderate implementation levels. This pattern indicates that while some advanced AI-BDA techniques are well established, others are still in the early adoption phases.

4.3.2. Exploratory Factor Analysis (EFA)

An EFA was performed using principal component analysis and varimax rotation, as shown in Table 3. The minimum factor loading criteria was set to 0.50, informed by Conway and Huffcutt's [107] study as the standard for determining meaningful loadings. The communality of the scale, which indicates the amount of variance in each dimension, was also assessed to ensure acceptable levels of explanation. The results show that all communalities were over 0.50.

A critical step involved weighing the overall significance of the correlation matrix through Bartlett's Test of Sphericity, which measures the statistical probability that the correlation matrix has significant correlations among some of its components. The results were significant, χ^2 (n = 200) = 62.890 ($p < 0.001$), which indicates its suitability for factor analysis. The Kaiser–Meyer–Olkin measure of sampling adequacy (MSA), which suggests the appropriateness of the data for factor analysis, was 0.831. In this regard, data with MSA values above 0.800 are considered appropriate for factor analysis. Finally, the factor solution derived from this analysis yielded four factors for the scale, which accounted for 67.753 per cent of the variation in the data.

Table 3. Exploratory factor analysis.

Rotated Component Matrix [a]				
	Component			
	1	**2**	**3**	**4**
TSF1	**0.528**			
TSF2	**0.754**			
TSF3	**0.661**			
EWS1		**0.660**		
EWS2		**0.876**		
EWS3		**0.925**		
LO1			**0.770**	
LO2			**0.575**	
LO3			**0.886**	
RM1				**0.990**
RM2				**0.538**
RM3				**0.705**

Extraction method: principal component analysis. Rotation method: Varimax with Kaiser Normalization. [a] Rotation converged in six iterations.

The four components identified as part of this EFA aligned with the theoretical proposition in this research. Component 1 includes items TSF1 to TSF3, referring to Time-Series Forecasting (TSF). Component 2 includes items EWS1 to EWS2, which represent Early Warning Systems (EWSs). Component 3 includes items LO1 to LO3, referring to Logistics Optimisation (LO). Finally, component 4 includes items RM1 to RM3, referring to Real-time Monitoring (RTM). Factor loadings are presented in Table 3 above.

4.4. Measurement Scales

4.4.1. Reliability Analysis

As shown in Table 4, the reliability analysis results demonstrate strong internal consistency across all constructs measured in the study of AI-BDA implementation in humanitarian supply chains.

Table 4. Reliability analysis.

Construct	No. of Items	Cronbach's Alpha
Humanitarian Supply Chain Resilience	4	0.79
Time-Series Forecasting (TSF)	3	0.81
Early Warning Systems (EWSs)	3	0.82
Logistics Optimisation (LO)	3	0.80
Real-Time Monitoring (RTM)	3	0.78
Technology Readiness (TR)	10	0.84

Source: SPSS (2024).

The reliability analysis results presented in Table 4 indicate strong internal consistency across all constructs examined in this study. The humanitarian supply chain resilience construct, measured using four items, demonstrates strong reliability with a Cronbach's Alpha of 0.79. Each of the AI-BDA application constructs—Time-Series Forecasting (TSF), Early Warning Systems (EWSs), Logistics Optimisation (LO), and Real-Time Monitoring (RTM)—exhibits high internal consistency, with Cronbach's Alpha values ranging from 0.78 to 0.82, reinforcing their suitability for further analysis. Additionally, the Technology Readiness (TR) construct, measured using 10 items, has a Cronbach's Alpha coefficient of 0.84, indicating excellent reliability.

4.4.2. Convergent Validity

As shown in Table 5, the AI-BDA techniques construct exhibits strong factor loadings across all twelve items, ranging from 0.72 (RTM1) to 0.96 (LO2). The minimum loading of 0.72 exceeds the recommended 0.50 threshold, ensuring that all items contribute significantly to the construct. The highest loading of 0.96 (LO2) indicates a near-perfect correlation with the underlying construct. Logistics Optimisation (LO) items display particularly high factor loadings, with LO1 (0.92) and LO2 (0.96) reflecting strong alignment with AI-BDA applications in supply chain efficiency. Similarly, Early Warning Systems (EWSs) items load strongly between 0.76 and 0.92, while Time-Series Forecasting (TSF) items consistently range from 0.83 to 0.88, demonstrating their reliability in capturing predictive analytics capabilities. Real-Time Monitoring (RTM) items also exhibit substantial loadings between 0.72 and 0.88. The Average Variance Extracted (AVE) value of 0.74 confirms that the construct explains 74% of the variance in its measured items, surpassing the 0.50 threshold for convergent validity.

Table 5. Convergent validity.

Construct	Item	Factor Loadings	Average Variance Extracted (AVE)
Humanitarian Supply Chain Resilience (α = 0.79)	HSCR1	0.87	0.75
	HSCR2	0.89	
	HSCR3	0.84	
	HSCR4	0.86	
Time-Series Forecasting (TSF) (α = 0.81)	TSF1	0.81	0.71
	TSF2	0.87	
	TSF3	0.85	
Early Warning Systems (EWSs) (α = 0.82)	EWS1	0.86	0.72
	EWS2	0.89	
	EWS3	0.80	
Logistics Optimisation (LO) (α = 0.80)	LO1	0.84	0.70
	LO2	0.88	
	LO3	0.86	
Real-Time Monitoring (RTM) (α = 0.78)	RTM1	0.79	0.69
	RTM2	0.85	
	RTM3	0.83	
Technology Readiness (TR) (α = 0.84)	TR1	0.87	0.73
	TR2	0.89	
	TR3	0.82	
	TR4	0.84	
	TR5	0.86	
	TR6	0.81	
	TR7	0.83	
	TR8	0.87	
	TR9	0.80	
	TR10	0.85	

For the Humanitarian Supply Chain Resilience (HSCR) construct, all four items demonstrate strong and uniform factor loadings, ranging from 0.84 to 0.89. The highest loading is observed for HSCR2 (0.89), followed by HSCR1 (0.87), HSCR4 (0.86), and HSCR3 (0.84), indicating that all items contribute robustly to the measurement of supply chain resilience. The AVE value of 0.75 suggests that the construct accounts for 75% of the variance in its measured items, reinforcing its strong convergent validity and exceeding the recommended 0.50 threshold.

Similarly, the individual AI-BDA application constructs—TSF, EWS, LO, and RTM—demonstrate high factor loadings across their respective items, with AVE values ranging from 0.69 to 0.72, confirming their strong explanatory power. Technology Readiness (TR), with an AVE value of 0.73, also exhibits strong validity, with item loadings between 0.80 and 0.89. These results collectively validate the reliability and robustness of the constructs, affirming their suitability for further analysis.

4.4.3. Discriminant Validity

As shown in Table 6, the discriminant validity analysis confirms strong construct distinction within the measurement model. Following the Fornell and Larcker [101] criterion, discriminant validity is established when the square root of the Average Variance Extracted (AVE) for each construct (diagonal values) exceeds its correlations with other constructs (off-diagonal elements). The results indicate that all constructs—HSCR, TSF, EWS, LO, RTM, and TR—satisfy this criterion, demonstrating that each construct measures a unique theoretical concept.

Table 6. Discriminant validity.

Constructs	HSCR	TSF	EWS	LO	RTM	TR
HSCR	**0.865**					
TSF	0.487	**0.846**				
EWS	0.475	0.525	**0.853**			
LO	0.498	0.522	0.544	**0.849**		
RTM	0.460	0.507	0.531	0.510	**0.835**	
TR	0.482	0.493	0.520	0.533	0.488	**0.854**

Source: SPSS (2024).

HTMT values below 0.85 (or 0.90 in some lenient cases) suggest good discriminant validity [99]. All values in Table 7 above are above 0.85, indicating that the constructs demonstrate adequate discriminant validity.

Table 7. HTMT ratios (discriminant validity assessment).

Constructs	HSCR	TSF	EWS	LO	RTM	TR
HSCR	**1.000**					
TSF	0.65	**1.000**				
EWS	0.61	0.74	**1.000**			
LO	0.63	0.71	0.70	**1.000**		
RTM	0.59	0.69	0.66	0.71	**1.000**	
TR	0.67	0.72	0.70	0.73	0.69	**1.000**

Source: SPSS (2024).

4.5. Effect of Artificial Intelligence and Big Data Analytics (AI-BDA) on Humanitarian Supply Chain Resilience

4.5.1. Diagnostic Test

Before the regression analysis was performed, a diagnostic test involving a multicollinearity and normality test was performed. Multicollinearity was assessed using variance inflation factors (VIFs). The normality test was assessed using the Shapiro−Wilk test. All variables, as shown in Table 8, demonstrate standard distribution patterns according to the Shapiro−Wilk tests. This is evidenced by non-significant p-values ($p > 0.05$) across all variables, which means that we cannot reject the null hypothesis, which states that the variable is normally distributed.

Table 8. Normality test.

	Kolmogorov−Smirnov [a]			Shapiro−Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
Time-Series Forecasting (TSF)	0.081	200	0.200 *	0.977	200	0.325
Early Warning Systems (EWSs)	0.069	200	0.200 *	0.983	200	0.419
Logistics Optimisation (LO)	0.073	200	0.200 *	0.985	200	0.468
Real-Time Monitoring (RTM)	0.065	200	0.200 *	0.988	200	0.527
HSCR	0.078	200	0.200 *	0.981	200	0.378
Technology Readiness (TR)	0.064	200	0.200 *	0.984	200	0.446
Organisation Size (OS)	0.089	200	0.132	0.979	200	0.354

Note: [a]: Test Distribution is Normal * Significance level at 0.200.

4.5.2. Hypothesis Testing

This section used regression analysis to test the hypotheses and compare the relationship between AI-BDA techniques and Humanitarian Supply Chain Resilience (HSCR). Table 9 shows the regression model summary findings, with the coefficient of determination indicating how much the predictor variable influences the dependent variable. Table 10 shows the analysis of variance, which shows how well the model describes the relationship, and Table 11 shows the regression coefficients, which show the magnitude of the effect of independent variables on the dependent variable.

Table 9. Model summary.

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	0.918 [a]	0.844	0.812	0.22561

[a] Predictors: (Constant), TSF, EWS, LO, RTM, OS, TR. Source: SPSS data (2024).

Table 10. Analysis of variance.

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	28.324	7	4.046	148.40	0.000 [b]
	Residual	5.235	192	0.027		
	Total	33.56	199			

[a] Dependent variable: HSCR. [b] Predictors: (Constant), TSF, EWS, LO, RTM, OS, TR. Source: SPSS data (2024).

Table 11. Regression results.

Model		Unstandardised Coefficients		Standardised Coefficients	t	Sig.	VIF
		B	Std. Error	Beta			
1	(Constant)	0.873	1.698		0.514	0.298	
	TSF	0.231	0.012	18.489	18.489	0.00	1.036
	EWS	0.186	0.012	15.611	15.611	0.00	1.036
	LO	0.230	0.013	17.333	17.333	0.00	1.056
	RTM	0.201	0.013	15.759	15.759	0.00	1.021
	OS	0.173	0.012	14.190	14.190	0.00	1.055
	TR	0.114	0.013	9.045	9.045	0.00	1.038

a. Dependent variable: HSCR. Source: SPSS data (2024).

The R-value of 0.918 suggests that the AI-BDA techniques—TSF, EWS, LO, RTM, OS, and TR—collectively have a strong influence on humanitarian supply chain resilience. The R-square is 0.844, as seen in Table 9. This means that the model's predictor variables explain 84.4% of the variance in HSCR. Other factors not included in the model account for the remaining 15.6% of the total variation in HSCR. Adjusted R^2 accounts for the number of

predictors in the model and adjusts for any potential overfitting. A value of 0.812 indicates that about 81.2% of the variance in HSCR is explained when considering the number of predictors.

The ANOVA test of the model's capability is shown in Table 10, with an F statistic of 148.40 and a significance of $p < 0.05$, indicating that the data file fits the model well. The model is statistically significant, indicating that the predictors collectively have a significant impact on Humanitarian Supply Chain Resilience (HSCR).

The VIF values for the predictors ranged from 1.056 to 1.021, as shown in Table 11, suggesting that multicollinearity is not a major concern in this model. The results in Table 11 indicate that AI-BDA techniques have a positive and significant effect on HSCR, highlighting the critical role of Artificial Intelligence and Big Data Analytics techniques in improving the resilience of humanitarian supply chains. TSF (B = 0.231, $p < 0.001$), EWS (B = 0.186, $p < 0.001$), LO (B = 0.230, $p < 0.001$), and RTM (B = 0.201, $p < 0.001$) have positive and significant effects on HSCR; hence, the alternate hypotheses ($H_{B1,}$ $H_{C1,}$ $H_{D1,}$ H_{E1}) are accepted.

Examining the relative effects of the AI-BDA techniques, the results reveal that Time-Series Forecasting (TSF) (B = 0.231, $p < 0.001$), Logistics Optimisation (LO) (B = 0.230, $p < 0.001$), and Real-Time Monitoring (RTM) (B = 0.201, $p < 0.001$) in order of significance also exhibit the strongest effects on HSCR, suggesting that predictive analytics, optimised logistics, and real-time tracking significantly contribute to enhancing the adaptability and efficiency of humanitarian operations.

Similarly, Early Warning Systems (EWSs) (B = 0.186, $p < 0.001$) and Organisation Size (OS) (B = 0.173, $p < 0.001$) show substantial effects, reinforcing the importance of organisational size in proactive risk identification and strategic decision-making in crisis management. However, Technology Readiness (TR) (B = 0.114, $p < 0.001$), while still statistically significant, has the weakest impact on HSCR, indicating that while readiness for technology adoption plays a role, its influence is relatively lower compared to other AI-BDA applications.

5. Discussion

5.1. Artificial Intelligence and Big Data Analytics (AI-BDA) Techniques Used in Humanitarian Supply Chains to Enhance Resilience

The results provided valuable insights into how AI-BDA techniques have evolved within humanitarian supply chains and their impact on resilience. The four main techniques—Time-Series Forecasting (TSF), Early Warning Systems (EWSs), Logistics Optimisation (LO) and Real-Time Monitoring (RTM)—are consistent with the theories proposed and have various degrees of adoption within humanitarian organisations.

The high adoption of early warning systems for pre-positioning supplies (EWS3) and multi-objective optimisation for resource allocation (LO2) are testaments to their effectiveness in strengthening supply chain resilience. This result is consistent with previous studies from Lamsal and Kumar [6], who highlighted the accuracy of machine learning algorithms to predict flood susceptibility prediction, and Harika et al. [108], who emphasised AI-enabled optimisation in the deployment of resources during crisis.

Though many studies have emphasised the potential value of these techniques [2,61], they also acknowledge the obstacles to adopting and deploying them. For example, Kusi-Sarpong et al. [109] cited data quality, interoperability, and algorithm stability as significant roadblocks to AI-BDA adoption in scalable supply chains. Given that techniques such as AI-based flood prediction systems (EWS2) and disaster risk prediction with machine learning (EWS1) have been under-utilised, this raises questions about the barriers to their implementation. These techniques have been proven effective in the literature [37]. Still,

their lower adoption in this analysis indicates that humanitarian organisations may face challenges regarding data availability, technical skills, or organisational capacity.

Another noteworthy finding is adopting relatively moderate Real-Time Monitoring techniques (RTM). While previous studies have stressed the need for real-time tracking and monitoring in humanitarian situations [61,62], the lower mean score for AI-based resource allocation monitoring (RM2) shows potential barriers to adoption. These might include data integration, infrastructure bottlenecks, or a requirement for specialised expertise.

Moreover, successfully adopting and implementing AI-BDA techniques requires a supportive organisational culture and alignment of technological capability with humanitarian values and objectives [9]. The socio-technical perspective emphasises the importance of considering both the technical and human aspects of AI-BDA implementation. This aligns with the STS Theory, which posits the need to combine social and technical components for optimal system performance [13,14]. For instance, varying adoption levels of AI-BDA techniques, including early warning systems and logistics optimisation, underscore the importance of a socio-technical approach considering technological capabilities and human capacities for successfully applying these techniques.

5.2. Effect of Artificial Intelligence and Big Data Analytics (AI-BDA) Techniques on Humanitarian Supply Chain Resilience

The findings of this study indicate that Artificial Intelligence (AI) and Big Data Analytics (BDA) significantly enhance Humanitarian Supply Chain Resilience (HSCR). The regression analysis results demonstrate that AI-BDA techniques, including Time-Series Forecasting (TSF), Early Warning Systems (EWSs), Logistics Optimisation (LO), and Real-Time Monitoring (RTM), contribute positively to HSCR. These findings align with previous studies that highlight the AI-BDA role in improving supply chain efficiency, decision-making, and responsiveness in disaster relief operations [2,25].

A key similarity between this study and prior research is the strong impact of predictive analytics on HSCR. Dubey et al. [2] argue that predictive analytics enhances disaster preparedness by forecasting demand and optimising inventory levels, reducing wastage and response times. Similarly, our study finds that TSF and EWS exhibit high factor loadings and significant contributions to resilience, reinforcing their value in humanitarian logistics.

Another major finding concerns the role of Logistics Optimisation (LO) in HSCR. The study reveals that LO is the most influential predictor among the AI-BDA techniques, consistent with the work of Queiroz and Pereira [110], who emphasise AI-driven logistics optimisation in reducing supply chain disruptions. This suggests that organisations should prioritise AI-based routing, scheduling, and resource allocation to improve response effectiveness.

Interestingly, the study found lower adoption rates for AI-based flood prediction systems (EWS2) and Real-Time Monitoring technologies (RTM) despite their proven effectiveness in the literature. Previous studies, such as those by Choi et al. [111], have found that RTM significantly enhances supply chain agility. This contradicts the theoretical expectations but aligns with Kusi-Sarpong et al. [109], who identified data quality, interoperability, and algorithm stability as significant barriers to AI-BDA adoption in supply chains. Humanitarian organisations likely face additional challenges related to data availability, technical expertise, and organisational capacity that hinder comprehensive AI-BDA implementation.

The findings also support the Resource-Based View (RBV) Theory, suggesting that organisations leveraging AI-BDA as strategic assets can enhance resilience. However, the study contradicts Bag et al. [77] by suggesting that implementation barriers may limit the AI-BDA effectiveness in humanitarian contexts compared to commercial supply chains.

From a practical perspective, these findings indicate that while AI-BDA significantly enhances HSCR, humanitarian organisations should focus on improving data quality, enhancing technical capabilities, and aligning technology with humanitarian objectives to maximise benefits. The study implicitly supports Beduschi [11] and Madianou [112] by suggesting that ethical considerations are essential when implementing AI-BDA in humanitarian contexts, requiring ongoing engagement between humanitarian agencies, technology providers, and affected communities.

5.3. Research Implications

The implications of these findings are substantial. First, humanitarian organisations should invest in AI-driven predictive analytics and logistics optimisation tools to enhance HSCR. Second, policymakers in developing economies must address technological barriers by improving digital infrastructure and fostering capacity-building initiatives. Lastly, supply chain managers should integrate AI-BDA solutions with existing response mechanisms to maximise resilience.

This research advances the theory by empirically validating the relationship between specific AI-BDA techniques and humanitarian supply chain resilience in developing economies. By integrating the Socio-Technical Systems Theory and Resource-Based View, we provide a more comprehensive understanding of how technological innovations enhance humanitarian operations. Our findings reveal that the effectiveness of AI-BDA varies by technique and context, suggesting that resilience theories should account for technological implementation factors when applied to humanitarian settings.

6. Conclusions

This study examined the effect of AI-BDA techniques on humanitarian supply chain resilience, focusing on key predictive analytics methods such as Time-Series Forecasting (TSF), Early Warning Systems (EWSs), Logistics Optimisation (LO), and Real-Time Monitoring (RTM). The findings indicate that AI-BDA techniques significantly enhance humanitarian supply chain resilience by improving demand forecasting, risk anticipation, logistics efficiency, and real-time response capabilities. Among these, TSF and LO demonstrated the strongest impact, reinforcing their critical role in proactive supply chain management. The study makes a significant contribution to the field by empirically validating the positive relationship between AI-BDA adoption and HSCR within developing economies, providing a framework for understanding which techniques are most effective in humanitarian contexts. It also highlights the practical implementation barriers that limit the AI-BDA full potential, emphasising the need for capacity building, data standardisation, and multi-stakeholder partnerships. By grounding the analysis in both Socio-Technical Systems Theory and Resource-Based View, this research advances the theoretical understanding of how technological innovations enhance humanitarian operations. These insights offer valuable guidance for humanitarian organisations seeking to leverage AI-BDA to improve disaster response effectiveness in resource-constrained environments.

6.1. Recommendations

Based on the findings, the following recommendations are proposed:

1. Given the lower adoption rates of real-time monitoring despite its proven effectiveness, humanitarian organisations should allocate resources to implement AI-driven tracking systems for improved supply visibility. This will enhance operational transparency, enable rapid response to disruptions, and support informed decision-making during crises. Organisations should focus on solutions that overcome connectiv-

ity challenges in disaster-prone areas, such as edge computing technologies and lightweight applications that can function in low-bandwidth environments.

2. To address the technical expertise gap identified in the study, organisations should establish comprehensive training programs focused on AI-BDA applications in humanitarian contexts. These programs should target both technical staff and operational decision-makers to build organisational readiness. Partnerships with academic institutions and technology companies can facilitate knowledge transfer while creating communities of practice across humanitarian agencies that will support shared learning and standardisation of AI-BDA implementation approaches.
3. To maximise the AI-BDA impact on supply chain resilience while addressing ethical concerns, humanitarian organisations should develop collaborative frameworks with technology providers, affected communities, and fellow humanitarian actors. These partnerships should focus on creating contextually appropriate ethical guidelines for AI-BDA deployment, ensuring data privacy protections, and designing transparent algorithmic systems that respect human rights. Special attention should be given to inclusive practices that ensure AI-BDA solutions benefit marginalised communities rather than reinforcing existing inequalities.

6.2. Limitations of the Study

The study gives valuable insights into how AI-BDA integration can be applied to humanitarian supply chains but presents multiple significant limitations. The study focused on Ghana and South Africa, as their geographical scope presents limitations for using their findings in different regions. Purposive sampling introduces selection bias, and the research design captures only a static view of AI-BDA deployment without tracking its progress over time.

The quantitative methodology of the study delivers measurable results but cannot thoroughly understand the complex social and organisational cultural factors that affect AI-BDA implementation. A mixed-methods research design that includes qualitative data would have uncovered more profound insights into implementation challenges and opportunities.

The research limits its scope by examining only humanitarian professionals' perspectives while neglecting to consider the insights of affected populations alongside technology providers and policymakers. Including various perspectives would have enabled a more thorough grasp of the ethical implications and social impact of AI-BDA in humanitarian situations.

6.3. Suggestions for Further Studies

Future research could explore the following areas to advance further the understanding of AI-BDA applications in humanitarian supply chains:

1. Conduct comparative studies across different geographic locations and humanitarian settings to uncover context-specific AI-BDA adoption and effectiveness.
2. Use longitudinal study designs to investigate AI-BDA interventions' long-term effects and sustainability in humanitarian supply chains.
3. Utilise mixed methods, including quantitative and qualitative, to holistically explore the social, organisational, and cultural dimensions of AI-BDA implementation.

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