EXPLORING THE CONVERGENCE OF ARTIFICIAL INTELLIGENCE AND BIG DATA ANALYTICS FOR RESILIENCE IN HUMANITARIAN SUPPLY CHAINS

BY

EMMANUEL AHATSI

Submitted in fulfilment of the requirements for the degree of

Doctor of Engineering (D.Eng.)

In the Department of Industrial Engineering,

Faculty of Engineering and the Built Environment

DECEMBER 2024

Declaration

I, Emmanuel Ahatsi, declare that this thesis is the original of my work and any published work of another person has been duly acknowledged and referenced. It has not been submitted for any degree or examination at any other university. This work is being submitted for the degree of Doctor of Engineering (D.Eng.) in the Department of Industrial Engineering.

05/04/2025

Emmanuel Ahatsi (22384754) **Date**

Approved for Final Submission by:

18/04/2025

Supervisor: Prof. Oludolapo A. Olanrewaju **Date**

Acknowledgements

I am profoundly grateful to the almighty God for His unending mercy and grace that strengthened me throughout my doctoral journey. His divine support has been the cornerstone of my achievements.

My deepest appreciation goes to my ever-supportive supervisor, Prof. O.A. Olanrewaju, for his immense support, guidance, and the opportunity to work under his esteemed tutelage. His mentorship has been invaluable in shaping my academic pursuits and professional growth.

I extend my heartfelt gratitude to my two big brothers, H.E. Ambassador Dr. Kodzo Kpoku Alabo and Dr. Reuben Mawuli Coffie, for their unwavering guidance, inspiration, and financial support. Their encouragement has been a driving force in my journey.

Special thanks to my lovely siblings for their unflinching support and motivation. Their belief in me has been a source of strength and comfort. A huge appreciation also goes to my beautiful wife, Ms. Oneria Otuko Kposu, and our two adorable kids, Winston and Evanthia whose unwavering love, support, and patience have been my constant source of strength and inspiration.

I am also grateful to my colleagues and peers who stood by me during this journey. In particular, Dr. Emmanuel A. Sawyerr of Cranfield School of Management, England, United Kingdom who gave me the initial push to begin my doctoral studies, and Ms. Gloria Amo-Duodu of Murdoch University, Perth, Australia for her ever-supportive, information-rich, and solution-oriented perspective throughout my doctoral journey at Durban University of Technology.

Finally, I thank the Durban University of Technology, especially the Department of Industrial Engineering, for the privilege, opportunity, and funding provided throughout my studies. This journey would not have been possible without their support.

Abstract

While there is great promise in AI-BDA applications revolutionising humanitarian operations through predictive analytics and resource optimisation, they are underexplored in disaster response contexts, especially in developing economies. The aim of this research was to evaluate current AI-BDA techniques and their effect on supply chain resilience in humanitarian settings focusing on Ghana and South Africa. The study employed an explanatory research design with a quantitative approach, analysing data from purposively sampled 200 supply chain professionals in Ghana and South Africa. Structured questionnaires measuring the implementation of four key AI-BDA techniques: Time-Series Forecasting (TSF), Early Warning Systems (EWS), Logistics Optimization (LO) and Real-time Monitoring (RTM) were used for data collection. Exploratory factor analysis and regression analysis were performed to analyse the relationship between AI-BDA techniques and supply chain resilience, controlling for organisational size and technological readiness. The results of the findings show that the AI-BDA techniques have significant effects on humanitarian supply chain's resilience with TSF and LO having the highest predictive power with technology readiness and organisational size facilitating the adoption of AI-BDA. Moreover, the findings revealed that resource-related barriers, particularly skill gaps among staff and lack of technical expertise, represent the most significant challenges to AI-BDA adoption. The study recommends implementing a holistic AI-BDA approach that aligns with humanitarian principles. This involves a multi-faceted strategy that not only emphasizes the ethical use of AI-BDA but also prioritizes personnel capacity building through tailored training programs. These programs should focus on enhancing technical skills, such as data analysis, machine learning algorithms, and ethical considerations in data usage. By integrating these elements, organizations can ensure that AI-BDA tools are utilized responsibly and effectively, ultimately leading to improved outcomes in humanitarian efforts while maintaining public trust and safeguarding individual rights.

Table of Contents

List of Figures

List of Tables

List of Acronyms

AI - Artificial Intelligence

AI-BDA - Artificial Intelligence and Big Data Analytics

ANOVA - Analysis of Variance

AVE - Average Variance Extracted

BDA - Big Data Analytics

DDDM - Data-Driven Decision Making

EFA - Exploratory Factor Analysis

EWS - Early Warning Systems

HOT - Humanitarian OpenStreetMap Team

HSCO - Humanitarian Supply Chain Operations

HSCR - Humanitarian Supply Chain Resilience

HSC - Humanitarian Supply Chain

ICT - Information and Communication Technology

IDT - Information and Digital Technology

IoT - Internet of Things

KPI - Key Performance Indicators

LO - Logistics Optimization

NGO - Non-Governmental Organization

OCHA - United Nations Office for the Coordination of Humanitarian Affairs

PLS-SEM - Partial Least Squares Structural Equation Modeling

PPP - Public-Private Partnership

RBV - Resource-Based View

RFID - Radio-Frequency Identification

RTM - Real-Time Monitoring

SARIMA - Seasonal Autoregressive Integrated Moving Average

SC - Supply Chain

SCM - Supply Chain Management

SCR - Supply Chain Resilience

SEM - Structural Equation Modeling

SPSS - Statistical Package for the Social Sciences

STS - Socio-Technical Systems

TB - Technical Barriers

TISM - Total Interpretive Structural Modeling

TSF - Time-Series Forecasting

UN - United Nations

UNHCR - United Nations High Commissioner for Refugees

WFP - World Food Programme

Research Outputs

This section presents publications that have been published/accepted/submitted.

Journals

Ahatsi, E., Nie, L., & Olanrewaju, O. A. (2024). Climate Change Mitigation and Adaptation in Ghana: Strategies and Challenges Faced by Social Enterprises. *Atmosphere 2024*, 15(11), 1278; https://doi.org/10.3390/atmos15111278

Ahatsi, E., Nie, L., & Olanrewaju, O. A. (2025). Empowering Humanitarian Efforts: A Dynamic Approach to Competitive Intelligence (CI). Logistics 2025, *9(1), 14;* https://doi.org/10.3390/logistics9010014

Ahatsi, E. & Olanrewaju, O. A. (2025). Evaluating the Effectiveness of Artificial Intelligence and Big Data Analytics in Enhancing Humanitarian Supply Chain Resilience. Logistics 2025, *In-Press Manuscript*

Conferences

Ahatsi, E., Akpan J., & Olanrewaju, O. A. (IHTC 2024). The Convergence of Artificial Intelligence and Big Data for Humanitarian Supply Chain Resilience. Presented at the *IEEE International Humanitarian Technologies Conference*, Bari, Italy (27-30 November 2024), doi: 10.1109/IHTC61819.2024.10855125

Ahatsi, E., Nie, L., & Olanrewaju, O. A. (2025). Climate Change Mitigation and Adaptation in Ghana: Strategies and Challenges Faced by Social Enterprises. *Presented at the 2nd International Conference of the ASEAN Social Work and Social Development 2025. Bangkok, Thailand (9 – 10 January 2025)*

Ahatsi, E., Nie, L., & Olanrewaju, O. A. (2025). Navigating the digital shift: E-procurement Adoption among Ghanaian small and medium enterprises. *Presented at the proceedings of the*

15th International Conference on Industrial Engineering and Operations Management (IEOM), February 18–20, 2025, Singapore. Singapore University of Social Sciences, In-press Manuscript

Ahatsi, E., Nie, L., & Olanrewaju, O. A. (IHTC 2025). Barriers to the Adoption of Artificial Intelligence and Big Data Analytics in Humanitarian Supply Chains: Exploring Two-Nation Context. Submitted to *IEEE International Humanitarian Technologies Conference*, Edmonton, Alberta, Canada (13-15 August, 2025)

Ahatsi, E., Akpan, J., & Olanrewaju, O. A. (SEGE 2025). Improving Photovoltaic Cells Parameter Estimates using AI – Overview and a Comparative Brief. Submitted to *SEGE 2025 (2025 IEEE the 13th International Conference on Smart Energy Grid Engineering)*, Ontario Tech University, Oshawa, Canada (August 18-20, 2025)

Ahatsi, E., Winkler, H., & Olanrewaju, O. A. (IHTC 2025). Achieving Resilience in Humanitarian Supply Chains: Targeted Applications of AI-Driven Big Data Analytics. Submitted to *IEEE International Humanitarian Technologies Conference*, Edmonton, Alberta, Canada (13-15 August, 2025)

Ahatsi, E., Winkler, H., & Olanrewaju, O. A. (IHTC 2025). Resilience in Humanitarian Supply Chains: The Role of Community-Led Initiatives. Submitted to *IEEE International Humanitarian Technologies Conference*, Edmonton, Alberta, Canada (13-15 August, 2025)

Ahatsi, E., Winkler, H., & Olanrewaju, O. A. (SEGE 2025). Modified Teaching-Learning Based Optimization for Resilience and Sustainability in the Renewable Energy Sector. Submitted to *SEGE 2025 (2025 IEEE the 13th International Conference on Smart Energy Grid Engineering)*, Ontario Tech University, Oshawa, Canada (August 18-20, 2025)

Ahatsi, E., & Olanrewaju, O. A. (ICTAS 2025). Tapping into the Digital Waves: Advancements and Trends in Ghana's Mobile Telecommunications Industry. Submitted to

ICTAS 2025 (2025 IEEE the 9th International Conference on Information Communication Technology and Society), Capital Zimbali Conference Centre, Ballito, KZN, South Africa (July 23-25, 2025)

Ahatsi, E., & Olanrewaju, O. A. (IEEM 2025). Assessing Supply Chain Risk Management in Ghana's Pharmaceutical Sector: A Situational Analysis. Submitted to *IEEM 2025 (2025 IEEM the International Conference on Industrial Engineering and Engineering Management)*, Melbourne Convention and Exhibition Centre, Melbourne, Australia (December 7-10, 2025)

CHAPTER ONE

INTRODUCTION

1.1 Background

The integration of Artificial Intelligence (AI) and Big Data Analytics (BDA) is a technique that is currently being used in numerous fields and has the potential to transform industries in the future (Ahmadi, 2024; Thayyib et al., 2023). These tools are becoming increasingly significant in supply chain management, especially in humanitarian supply chains (HSCs) (Rege, 2023; Smyth et al., 2024). Humanitarian Supply Chain Operations (HSCO) are crucial in delivering aid to the needy and vulnerable people during disasters, epidemics, and conflicts (Dubey, 2021; Taleghani & Gheibdoust, 2024). However, these operations are highly vulnerable and unpredictable (Dubey et al., 2014; L'Hermitte et al., 2016). This calls for developing new strategies to help in the decision-making process, resource management, and resilience. For this reason, integrating AI and BDA in HSCO is a viable approach to offer unique solutions that may help overcome the challenges and risks present in humanitarian logistics (Kahn et al., 2019; Zamani et al., 2023).

Conventional HSCs have been characterised by essential technologies and practices in distributing aid and managing resources (Malhouni & Mabrouki, 2022). Although these methods can be helpful in some scenarios, they are weak and unsustainable in the face of big disasters which need timely interventions and flexibility (Argollo da Costa et al., 2014; Seifert et al., 2017). Sophisticated systems that can handle large amounts of data and control complex logistics are needed to respond to disasters quickly and efficiently. Furthermore, these approaches to humanitarian crises are primarily reactive or, at best, anticipatory rather than predictive to address future requirements through forecasting (Altay & Narayanan, 2020; Malhouni & Mabrouki, 2022). This view of the integration of AI and BDA is, therefore, an enhanced advancement in the humanitarianism space because it presents new ways of improving and enhancing the analysis of data and making better predictions as well as decisions in comparison to the traditional humanitarian systems (Dennehy et al., 2021; Dubey et al., 2022; Zamani et al., 2023).

AI comprises technologies such as machine learning, natural language processing and computer vision, which can simulate human intelligence, analyse large amounts of data and make decisions based on such information (Gallego et al., 2021; Sun et al., 2021). In humanitarian endeavours, AI technology can predict the impacts of disasters, enhance readiness, optimise supply routes, and improve resource allocation (Bari et al., 2023; Velev & Zlateva, 2023). Moreover, AI can provide decision support systems that can assist humanitarian agencies in real time, ensuring pre-emptive actions and strategic resource positioning so that resources are directed to where they are needed most timely and efficiently (Pizzi et al., 2020).

On the other hand, BDA involves processing and analysing large datasets to identify trends, associations, and insights that can inform strategic decisions (Sivarajah et al., 2017). Concerning HSCO, BDA can enhance the awareness of situations by integrating different datasets such as satellite imagery and social media, which help to gain more accurate information on operational environments, assisting in proper planning and execution of relief efforts (Kondraganti, 2021; Yakobi et al., 2020). BDA can also help identify anomalies that may suggest emerging issues, and faster and more proactive responses can be engaged (Dubey et al., 2019).

Combining AI and BDA into HSCO could be a turning point in humanitarian operations since it can enhance agility and resilience. Thus, AI-powered predictive analytics can forecast disruptions and facilitate proactive measures, while BDA provides the detailed insights necessary for informed decision-making (Dubey et al., 2019, 2020, 2022). In an era marked by increasing natural disasters and humanitarian crises, the efficiency and resilience of HSCs play a critical role in saving lives (Xu et al., 2023; Yadav & Barve, 2015). This research investigates the integration of BDA and AI in HSCs to enhance supply chain resilience. It addresses a significant problem: how to improve the effectiveness of HSCs through digital enhancements.

1.1.1 The Concept of Humanitarianism: An Overview

The concept of humanitarianism dates back centuries. In modern history, Henri Dunant is credited as the father of organised humanitarianism and the founder of the International Red Cross and Red Crescent Movements (Shafiq & Soratana, 2019). Dunant sacrificially and compassionately treated the wounded soldiers of the Battle of Solferino in Italy in 1859. As a result, the core objectives of humanitarian organisations are to respond to disasters, uphold human rights, offer relief services, and advance the common desire for individual and societal safety, security, respect, and dignity without regard for profit (Shafiq & Soratana, 2019). Thus, actively giving aid to prevent death, reduce suffering, and restore and advance human dignity in the wake of large-scale emergencies and disasters constitutes humanitarian action (Pringle & Hunt, 2015).

There are four cardinal principles of humanitarianism: humanity, neutrality, impartiality and independence. These principles were legally codified in 1991 (humanity, impartiality, and neutrality) and in 2004 (independence) by the UN General Assembly (Rysaback-Smith, 2015). All humanitarian action is based on the fundamental idea of humanity. The idea that it should come first over all other ideas and beliefs is commonly held since it expresses the reason for humanitarian action, which is to alleviate human suffering (Lauri, 2021). However, humanity without impartiality remains an empty principle; therefore, the humanity principle cannot stand alone or serve as the only basis for making decisions. All humanitarian assistance must be targeted at people in need and given to the most critical cases of need. It must not be discriminated against based on the nationality, ethnicity, gender, religion, social status, or political affiliation of the targeted people (Norwegian Refugee Council, 2016). In addition, humanitarians are not allowed to take a stand and support one side in a conflict that is either political, racial, religious or ideological, which shows the principle of neutrality that has to be adhered to (Prodromou & Symeonides, 2016; Rysaback-Smith, 2015). Lastly, humanitarian actions must be neutral and devoid of political, economic, military or any other intentions of the actors involved in the region where the humanitarian actions are being implemented (Norwegian Refugee Council, 2016). Absolute neutrality can only be achieved when political or economic force does not influence one.

Antonio De Lauri argues humanitarianism goes beyond just responding to a crisis (Lauri, 2021). He considers humanitarianism as a 'modality of intervention' comprising a broad, well-organised, dynamic, and multi-scale web of players, politics, and institutions, with a moral belief to address human needs and improve the world. Today's humanitarian aid is multifaceted, with thousands of non-governmental organisations (NGOs) and other groups from many nations offering a range of assistance and development initiatives (Rysaback-Smith, 2015). Moreover, media outlets and social media extensively cover many crises, such as natural disasters and conflicts, and the internet makes it simple for people to organise, communicate, and raise money (Ruth et al., 2024; Scott et al., 2022). This growth has influenced assistance delivery positively and negatively, and it is expected to have a significant impact well into the future.

Some situations that have received humanitarian interventions include natural disasters such as earthquakes, tsunamis, volcanic eruptions, fire outbreaks and pandemics. However, the number of people needing humanitarian aid has significantly increased over the past few decades. For instance, in 2022 alone, the number was estimated to be 279 million, an increase that has been attributed to factors such as the COVID-19 global pandemic and wars such as the Russia-Ukraine and the Sudan wars (Anjomshoae et al., 2023). Others include the effect of climate change that has led to cases of droughts or extreme rainfalls that lead to fires or floods, respectively. Currently, the United Nations has put the figure at one in every twenty-two persons globally deserving humanitarian assistance, which amounts to 362 million people (United Nations, 2022). Besides, about 262 million people suffer from severe food insecurity, and some of them may even be starving.

In comparison, more than 110 million people have been displaced, as noted in the same report. These statistics are expected to keep increasing owing to economic instability, climate change and conflicts. These figures underscore the importance of healthy humanitarian activities. The demand for assistance is rising due to conflicts, climate change, and economic instability (United Nations, 2022).

However, the humanitarian sector is marked by extreme uncertainty, a continual need to adapt to unforeseen circumstances, and ideas and methods that frequently defy clear-cut definitions. It is, therefore, imperative to develop robust and resilient humanitarian supply chain systems that can help cater to the many people who need to avoid human suffering.

1.1.2 Humanitarian Logistics and Supply Chain Systems

Humanitarian logistics and supply chain management are similar to corporate and supply chain management. However, it does not involve manufacturing. The term "humanitarian logistics and supply chain systems" describes the specific procedures and techniques used to effectively coordinate the acquisition, movement, and distribution of products and services in the wake of pandemics, natural disasters, and other humanitarian emergencies, with the primary objective of maximising the utilisation of scarce resources while promptly and effectively helping people in need (Seifert et al., 2017; Shafiq & Soratana, 2019). Humanitarian logistics and supply chain management encompass various tasks, such as planning, organising, procurement, transporting, storing, monitoring, tracing, and obtaining customs clearance from the place of origin to the destination (Shafiq & Soratana, 2019). Kembro et al. (2024) consider humanitarian logistics (HL) as the process of preparation of and response to a humanitarian crisis, recovery of the affected population, and aims at saving lives and mitigating the sufferings of the population. However, Nikbakhsh & Zanjirani Farahani (2011) argue that the humanitarian logistics structure can be categorised into three main stages: supply acquisition and procurement, prepositioning and warehousing, and transportation, as depicted in Figure 1.1 below. However, that is just a general classification since it takes more than these three phases to ensure efficient HSCs. The following sections discuss these stages of the humanitarian supply chain and other relevant processes.

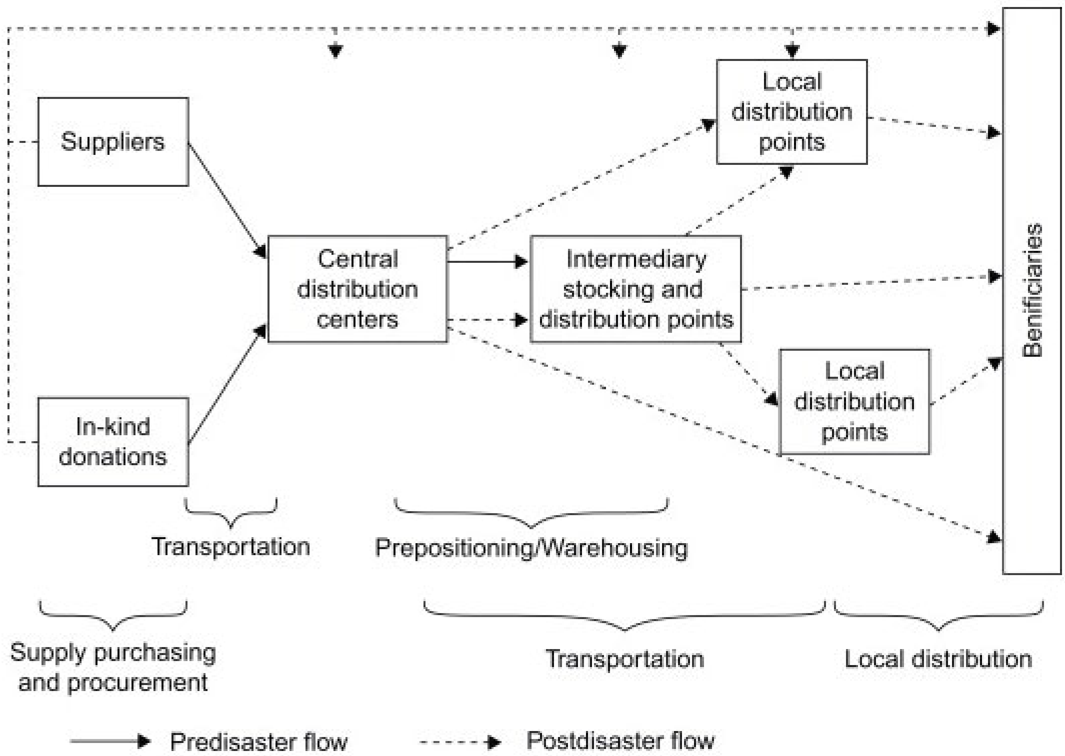

Figure 1.1 The humanitarian logistics chain structure (Source: Nikbakhsh & Zanjirani Farahani, 2011)

1.1.2.1 Procurement and Sourcing in Humanitarian Logistics and Supply Chains

The procurement and sourcing begin the humanitarian logistics supply chain and focus on acquiring goods and services needed for relief activities (Moshtari et al., 2021). This phase comprises vendor selection and contract management.

Selecting vendors entails finding trustworthy vendors offering necessities like food, water, medical supplies, and shelter and forming partnerships with them (Hu et al., 2022; Lamenza et al., 2019). This process is crucial to guaranteeing supply quality, availability, and timely delivery, and it is a very challenging step (Moshtari et al., 2021). To determine the precise needs of the impacted population and the kinds of commodities needed, a comprehensive needs assessment is carried out as the first phase in the vendor selection process (Lamenza et al., 2019).

The next step is market research, which examines possible suppliers' qualifications, standing, and previous track record in comparable situations (Lamenza et al., 2019; Shafiq & Soratana, 2019). Pre-qualification of suppliers is predicated on product excellence, delivery capacity, dependability, and morality, which are frequently confirmed by site visits and inspections (Hu et al., 2022; Moeiny & Mokhlesi, 2011). In the assessment and choice procedure, vendors are compared according to their offers, costs, delivery schedules, and compliance with quality criteria. Finally, a risk assessment is carried out to determine which vendors have robust risk management procedures and to examine the risks related to each vendor, such as financial instability or disruptions in the supply chain (Saıah et al., 2023).

Following the selection of vendors, it is crucial to use contract management to create detailed and thorough agreements that make sure all parties are aware of their responsibilities (Hu et al., 2022). Writing comprehensive contracts with delivery conditions, expenses, quality requirements, and deadlines, as well as incorporating provisions to handle contingencies like delays or shortages, is the first step toward effective contract management. It is critical to provide precise terms and conditions for delivery dates, packaging specifications, payment schedules, and inspection protocols (Lamenza et al., 2019). Contracts include quality assurance procedures, which frequently call for third-party certifications and inspections to guarantee that the products fulfil criteria.

Performance monitoring is essential to evaluate vendor performance through routine reviews and audits. Key performance indicators (KPIs) and defined metrics should be used (Moshtari et al., 2021; Pereira et al., 2014). Provisions for dispute resolution, such as arbitration or mediation, address conflicts that may arise. Moreover, ensuring adherence to legal and regulatory mandates, such as labour laws and environmental standards, is of paramount importance while also obtaining regular vendor reporting on delivery status and obstacles faced (Lamenza et al., 2019).

1.1.2.2 Transportation and Distribution in HSCs

After procurement, the next crucial phase is transporting relief items to the various distribution points or outlets. Transportation and distribution involve careful logistics planning and the utilisation of many means of transportation to meet the particular challenges of emergency situations (Safeer et al., 2014).

Logistics planning is the key to effective distribution and transportation in humanitarian operations (Regis-Hernández & Mora, 2015). Creating robust plans requires considering various elements, including accessibility, security threats, and infrastructure damage. Roads, bridges, and other transportation infrastructure may sustain significant damage following a disaster, requiring other routes and backup preparations (Munyaka & Yadavalli, 2021). To protect the security of the supplies and the logistics staff, security threats, such as those associated with unstable political conditions or combat zones, must be evaluated. Innovative solutions are needed to address accessibility problems, including distant or remote places, to reach the impacted populations (Munyaka & Yadavalli, 2021; Safeer et al., 2014). Coordinating with local government agencies and other humanitarian groups is another aspect of logistics planning that helps to guarantee a coordinated response and prevent duplication of effort (Regis-Hernández & Mora, 2015).

The selection of transport modes is contingent upon several factors, including urgency, distance, and topography, with air, sea, and land transportation all essential (Argollo da Costa et al., 2014; Zhang et al., 2011). Air transport is frequently employed for urgent delivery, particularly for high-priority or perishable goods like food and medical supplies (Albergaria et al., 2021). Though it can be expensive and dependent on the availability of airports or landing strips, it is beneficial for swiftly accessing remote or unreachable locations (Albergaria et al., 2021; Munyaka & Yadavalli, 2021). Sea transport provides affordable options for moving big loads of products across long distances, making it perfect for bulk shipments (Blank, 2021). However, it can be slower than the other approaches because it needs ports to be operational (Blank, 2021). However, transporting supplies from ports and airports to ultimate destinations requires land transportation, such as trucks and trains (Regis-Hernández & Mora, 2015). Although it may encounter obstacles due to destroyed infrastructure or security concerns, it is adaptable and capable of navigating a range of terrains (Argollo da Costa et al., 2014). Frequently, a blend of these approaches is employed to maximise effectiveness and guarantee prompt delivery (Zhang et al., 2011).

1.1.2.3 Warehousing and Inventory Management in HSCs

When relief items and equipment are transported, they are typically stored in warehouses at distribution centres close to beneficiaries before the items are distributed to them (Nikbakhsh & Zanjirani Farahani, 2011). This process involves strategic stockpiling and careful inventory tracking.

Stockpiling keeps supplies of necessities in key places to enable quick deployment in an emergency (McCoy & Brandeau, 2011). Usually, these supplies consist of food, water, medicine, building materials, and other necessities needed for quick relief operations. Stockpiling is a preventative strategy that enables humanitarian groups to react swiftly to emergencies by reducing delays brought on by transportation and procurement (Liu et al., 2016). Warehouses must be placed strategically, with sites selected according to defined criteria, including security, accessibility, and proximity to disaster-prone areas (Roh & Kim, 2016). This helps reduce the time it takes for aid to get to the needy, as supplies can quickly be dispatched to the affected regions. To ensure that the supplies are available and in proper condition at the required time, they must be restocked and updated from time to time (McCoy & Brandeau, 2011).

Additionally, inventory tracking involves installing systems to monitor expiration dates, stock levels, and the flow of items into and out of warehouses throughout the supply chain. Humanitarian organisations need accurate and current information about the availability and status of supplies, and effective inventory tracking ensures that that is done (Balcik et al., 2016). This is carried out using technologies like inventory management software, RFID tags, and barcode scanning to keep track of stock levels in real-time (Baldini et al., 2011; Chanchaichujit et al., 2020). For perishable goods like food and medical supplies, keeping track of expiration dates is crucial to preventing the distribution of outdated goods and maximising resource utilisation (Mora-ochomogo et al., 2016). Furthermore, monitoring the flow of commodities guarantees that they arrive at their intended locations and reduces the risk of theft, loss, and misallocation of resources (Balcik et al., 2016).

1.1.3 Other Necessary Processes for Humanitarian Logistics and Supply Chains

Besides the three primary stages of the humanitarian supply chain, some other vital processes or tools make the process smooth and effective in ensuring that humanitarian objectives are achieved. These processes include Information and Communication Technology (ICT), Risk Management and Flexibility, Coordination and Collaboration, and Evaluation and Continuous Improvement. The following section elaborates on these processes in detail.

1.1.3.1 Information and Communication Technology (ICT)

Looking at the multi-layered nature of HSCs, ICT is an almost indispensable tool if we desire efficiency. By leveraging advanced technologies, humanitarian organisations can handle data, coordinate operations, and guarantee the timely delivery of supplies (Marić et al., 2022). ICTs are most critical in the area of data management.

With specialised software, organisations can gather, examine, and distribute vital data regarding inventory levels, delivery schedules, and supply requirements (Ghadge, 2023). To precisely determine the needs of impacted populations, data collection entails obtaining current information from various sources, including field reports, sensors, and satellite photography (Kabra & Anbanandam, 2015; Marić et al., 2022). Analysing such data helps find patterns, estimate demand, and allocate resources strategically. Moreover, to guarantee a coordinated response, information dissemination requires sharing updates and insights with pertinent stakeholders (Ghadge, 2023). Sound data management systems ensure that resources are used effectively and go to those who need them quickly, enhancing accountability and transparency (Ghadge, 2023; Kabra & Anbanandam, 2015). Using ICTs, humanitarian organisations can anticipate difficulties, reduce duplication, and optimise their operations by keeping accurate and up-to-date data (Ghadge, 2023).

Furthermore, ICTs are also vital in coordinating platforms of humanitarian efforts. Coordination platforms allow all humanitarian stakeholders, such as governments, non-governmental organisations (NGOs) and local communities, to communicate and work together more easily (Marić et al., 2022). These platforms act as centralised centres where interested parties can communicate, organise interventions, and plan courses of action (Mubaraka et al., 2013). Currently, the most important platforms for mapping, information sharing, and collaborative planning are the Humanitarian OpenStreetMap Team (HOT), ReliefWeb, and Logistics Cluster (Jahre & Jensen, 2010; Sokat et al., 2016). These platforms facilitate effective responses to changing needs and allow stakeholders to follow the movement of commodities and supply chain operations. Coordination systems improve the overall responsiveness of humanitarian activities and augment situational awareness by promoting real-time communication (Jahre & Jensen, 2010; Marić et al., 2022).

1.1.3.2 Collaboration

The nature of humanitarian activities also makes them difficult for just one party to do. Therefore, they usually involve the coordinated efforts of different organisations or agencies such as the United Nations, NGOs, local governments and community groups. Efficient cooperation between these organisations facilitates the streamlining of operations, minimises duplication, and guarantees that assistance reaches the most susceptible groups (Wagner & Thakur-Weigold, 2018). A classic example of institutions involved in collaboration and coordination is the United Nations Office for the Coordination of Humanitarian Affairs (OCHA), which is essential (McLachlin & Larson, 2011). Such groups offer forums for information exchange, collaborative planning, and resource distribution, guaranteeing that all endeavours are directed toward shared objectives (Prasanna & Haavisto, 2018). Activities are coordinated, and response gaps are filled with common databases, collaborative planning tools, and regular coordination meetings (Prasanna & Haavisto, 2018; Wagner & Thakur-Weigold, 2018; Zain & Zahari, 2020).

Coordination and cooperation in humanitarian logistics are further improved by public-private partnerships (PPPs). Alongside the efforts of humanitarian organisations, the private sector may provide invaluable resources, creative ideas, and knowledge (Qiao et al., 2010; Zain &

Zahari, 2020). Partnerships with private businesses can also increase supply chain efficiency, increase logistics capabilities and give access to cutting-edge infrastructure and technologies (Diehlmann et al., 2021; Qiao et al., 2010). Again, such collaborations with logistics companies can facilitate the utilisation of their distribution networks, whereas partnerships with technological corporations can propel the advancement of data management and communication solutions (Diehlmann et al., 2021). PPPs create synergies that improve humanitarian operations' total capacity and enable quicker and more efficient reactions (Qiao et al., 2010).

1.1.3.3 Risk Management and Flexibility

Risk management is another essential element of the humanitarian logistics and supply chain. It is vital in predicting and preventing occurrences that may hinder the timely supply of aid (Emrouznejad et al., 2023). This requires recognising hazards like supply chain interruptions, natural disasters, armed conflict, and logistical difficulties (Minguito & Banluta, 2023). Some strategies include diversifying supply sources, keeping emergency supplies on hand, and creating thorough transportation plans that consider potential infrastructure damage (Emrouznejad et al., 2023; Minguito & Banluta, 2023). Organisations may ensure that they can quickly react to changing situations by preparing for numerous possibilities through regular risk assessments and scenario planning.

On the other hand, humanitarian logistics must be flexible to guarantee that organisations can react to changing and erratic circumstances quickly and efficiently (Tukamuhabwa et al., 2015). Flexibility allows logistics plans to be adjusted in reaction to fresh data or evolving conditions (Chowdhury et al., 2024). For example, combining land, sea, and air transportation enables last-minute changes based on infrastructure availability, urgency, and topography (Zhang et al., 2011). The ability to scale up or down operations as needed is also improved by adaptable partnerships and collaboration with various stakeholders, including local communities and private sector partners (Chowdhury et al., 2024). Additionally, adopting cutting-edge technology and procedures promotes increased agility, quicker decision-making, and more effective use of available resources (Zamani et al., 2023).

1.1.3.4 Evaluation and Continuous Improvement

One other essential process of the humanitarian supply chain is evaluation. There must be frequent evaluations to ensure continuous improvement and avoid repetitive mistakes or errors. Performance criteria, including beneficiary satisfaction, cost-effectiveness, resource utilisation, and delivery timelines, are used in the review process to determine how well logistics operations are doing (Santarelli et al., 2015). Periodic reviews assist in identifying areas of strength, highlighting regions in need of development, and guaranteeing that aid is provided in a way that satisfies the requirements of impacted populations (Anjomshoae et al., 2022). Surveys, audits, and feedback sessions with stakeholders and recipients are used to perform evaluations (Anjomshoae et al., 2022; Santarelli et al., 2015). These assessments show where changes are needed and offer vital information about how sound logistics operations are running.

In addition, every efficient humanitarian supply chain system tries to ensure continuous improvement. The constant endeavour is to improve logistics procedures considering evaluation results (Anjomshoae et al., 2022). Continuous improvement covers putting best practices into effect, making adjustments to solve gaps that have been found, and utilising cutting-edge technologies (Marciniak & Sienkiewicz-Małyjurek, 2022). A culture of learning and adaptability is fostered by continuous improvement, where feedback loops are set up to incorporate lessons from past events into future planning (Anjomshoae et al., 2022). This proactive strategy includes using new technology for improved data administration and communication, improving staff abilities through training and capacity-building programs, and honing logistical tactics to better adapt to changing conditions (Santarelli et al., 2015). Constant improvement makes humanitarian organisations more adaptable and responsive, which improves their capacity to provide relief in a timely and efficient manner.

1.2 Problem Statement

Given the rising and more frequent global crises, HSCs help provide timely and effective aid. However, these operations are inherently complex and risky, which presents a significant concern in disaster response and relief management (Behl & Dutta, 2019). The integration of AI and BDA can provide a solution to these challenges and may probingly transform conventional relief operations and strengthen the HSCs' resilience (Dubey et al., 2021).

Although AI and BDA have a high potential in humanitarian settings, their use is still limited and not well-researched. The current literature on the efficiency of using AI-BDA in humanitarian operations is still quite dispersed, and scholars have different points of view on some aspects of the operations and the theories underpinning them. This fragmentation is apparent in the current studies that are more concerned with theoretical frameworks than real-world implementations. For example, Dubey et al. (2022) propose using the practice-based view theory in examining AI-BDA in humanitarian operations, comparing it with other approaches employing a resource-based view or dynamic capability theory. Although many theoretical analyses of this subject can be helpful, they seldom address the importance of practical application in real-life scenarios.

Despite their high potential for humanitarian use, the applications of AI and BDA are still limited and under-researched. In previous studies, AI and BDA have been explored in the context of supply chain management, particularly in commercial logistics and industrial applications (Dennehy et al., 2021; Rege, 2023). Moreover, a limited number of studies have investigated how AI and BDA are utilized to enhance supply chain resilience in humanitarian operations, primarily presenting theoretical frameworks and case-specific applications (Dubey et al., 2022; Abhulimen & Ejike, 2024). For instance, Dubey et al. (2022) adopted the practice-based view as a theoretical framework to understand the impact of AIBDA on HSCR but failed to account for the different AIBDA techniques that affect HSCR. Abhulimen & Ejike (2024) accounted for the different AIBDA techniques but its focus was on presenting a systematic review on studies and case examples failing to present a data-driven evidence to substantiate the integration of AI and BDA functions in HSCs 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.

However, some challenges arise when integrating AI and BDA into HSCOs. Several technical and organisational challenges hinder their use in various fields. Such challenges involve data quality, interoperability, and the stability of the algorithms when dealing with chaotic data typical of humanitarian interventions (Beduschi, 2022; Cai & Zhu, 2015). Moreover, most humanitarian organisations do not have the technical background to properly deploy and manage such sophisticated systems (Kusi-Sarpong et al., 2021; Sharma & Joshi, 2019). Identifying and tackling these barriers is essential, as it will help effectively implement the AI-BDA solutions in HSCs. However, this area in current research has little empirical evidence (Jain et al., 2023; Kabra et al., 2023; Shrivastav, 2022), which this study also sought to fill.

1.3 Aim and Objectives of Study

1.3.1 Aim

To identify and evaluate specific applications of AI and BDA that effectively enhance humanitarian supply chain resilience (HSCR), focusing on developing practical, scalable solutions to address critical challenges in disaster response and resource distribution.

1.3.2 Specific Objectives

This current research seeks to achieve the following objectives:

1. To investigate the existing techniques of AI-BDA in HSCR.

2. To examine the effects of AI-BDA techniques on HSCR.

3. To identify and analyse the barriers in adopting and implementing AI-BDA within HSCs.

4. To provide recommendations for best practices in leveraging AI-BDA to strengthen HSCR in future crises.

1.4 Research Questions

The study sought to answer the following research questions:

1. What are the existing techniques of AI- BDA in HSCs in enhancing resilience?

2. What are the effects of AI-BDA techniques on the resilience of HSCs?

3. What challenges and barriers exist in adopting and implementing AI- BDA within HSCs?

4. What best practices can be recommended for leveraging AI- BDA to strengthen the resilience of HSCs in future crises?

1.5 Hypothesis

H_{A0}: AI-BDA techniques will not have a positive effect on HSCR.

H_{A1}: AI-BDA techniques will have a positive effect on HSCR.

H_{B0}: Time-Series Forecasting (TSF) will not have a positive effect on HSCR.

H_{B1}: Time-Series Forecasting (TSF) will have a positive effect on HSCR.

H_{C0}: Early Warning Systems (EWS) will not have a positive effect on HSCR.

H_{C1}: Early Warning Systems (EWS) will have a positive effect on HSCR.

H_{D0}: Logistics Optimization (LO) will not have a positive effect on HSCR.

H_{D1}: Logistics Optimization (LO) will have a positive effect on HSCR.

H_{E0}: Real-time Monitoring (RTM) will not have a positive effect on HSCR.

H_{E1}: Real-time Monitoring (RTM) will have a positive effect on HSCR.

1.6 Research methodology

The research employed a positivist paradigm to examine how Artificial Intelligence and Big Data Analytics (AI-BDA) can enhance humanitarian supply chain resilience. This approach was chosen because it enables systematic data collection and quantitative analysis to understand the effectiveness of AI-BDA applications in humanitarian operations.

The study used an explanatory research design to analyze the cause-and-effect relationships between AI-BDA applications and supply chain resilience measures. This design aligns with the positivist paradigm and allows for testing hypotheses through statistical analysis of how specific AI-BDA applications impact different components of humanitarian supply chain resilience.

The target population comprises supply chain management professionals directly involved in disaster response and relief in Ghana and South Africa, including supply chain managers, data scientists, IT specialists, and operational leaders. Using purposive sampling, 200 professionals with at least three years of experience in humanitarian supply chains and involvement in AI-BDA projects were selected.

Data collection was conducted through an online survey using Google Forms. The questionnaire included structured close-ended questions and Likert scales to gather information about AI-BDA techniques, their effectiveness, and implementation challenges. The survey instrument was pre-tested with 30 experts to ensure question comprehension and accuracy.

The study employed multi-item scales to measure theoretical constructs, with items adapted from previous research. Validity was ensured through expert review, construct validity assessment (using Average Variance Extracted), and face validity checks. Reliability was measured using Cronbach's alpha coefficient, with values above 0.7 considered satisfactory.

Data analysis involved several steps using SPSS version 27.0. Initial analysis included normality and multicollinearity testing. For the first research objective, means, standard deviations, and exploratory factor analysis were used to examine existing AI-BDA techniques. The second objective employed regression analysis to assess the effectiveness of AI-BDA applications on supply chain resilience. The third objective utilized factor analysis and descriptive statistics to identify implementation barriers.

The research adhered to ethical considerations throughout, including obtaining informed consent, ensuring participant confidentiality, and protecting data privacy. The study followed Durban University of Technology's ethical procedures and international research standards. These measures ensured participant rights were protected while maintaining research integrity and quality.

1.7 Significance and contribution of study

This study has vital implications in terms of contributions to bridging the gaps in literature and providing practical recommendations for integrating AI and BDA applications in humanitarian operations. Thus, the importance of this research is underscored by its potential to revolutionise humanitarian operations. By harnessing BDA and AI, the study aims to shift HSCs from being reactive to anticipatory and predictive (Beduschi, 2022; Dubey et al., 2020). It shall produce empirical evidence on how AI and BDA can affect humanitarian operations and how such tools can be applied for maximum efficiency and impact in HSCO.

The study's findings will contribute to the academic knowledge base on AI-BDA in HSCs. Through publications in high-quality academic journals and conference presentations, these findings enhance and create the platform for more in-depth research and scholarly discourse on AI-BDA humanitarian operations. Additionally, the findings of this research may lead to the development of educational materials and resources that can benefit students and professionals in humanitarian operations and supply chain management.

Furthermore, by evaluating how AI and BDA can be applied to HSCO, we can find out what these technologies have to offer in making humanitarian operations easy, quick and efficient, as well as dealing with the multifaceted challenges encountered in these operations (Velev & Zlateva, 2023). This research provides a detailed understanding of the potential of these technologies to transform humanitarian logistics. Thus, the findings of this research could serve as a helpful resource or reference to help humanitarian organisations optimise their operations. This would result in improved disaster preparedness and response strategies, reducing the negative impacts of humanitarian crises. The applicability of AI-BDA in humanitarian operations could result in more efficient and effective disaster response efforts, positively influencing community development in the African continent and possibly the entire globe. Thus, humanitarian organisations in Africa and the broader region are expected to apply the research insights to enhance their resilience in disaster response, leading to improved outcomes for affected communities.

Finally, this research may facilitate capacity-building efforts, equipping humanitarian organisations with the knowledge and tools needed to navigate the challenges of modern supply chain management in the context of disasters.

1.8 Scope of the study

The scope of this study focused on examining the implementation of AI-BDA in HSCs within Ghana and South Africa. The research specifically investigates three key areas: existing AI-BDA techniques (Time-Series Forecasting (TSF), Early Warning Systems (EWS), Logistics Optimization (LO) and Real-time Monitoring (RTM)), their effects on supply chain resilience, and barriers to implementation.

The geographical scope is justified by several factors. First, both Ghana and South Africa represent significant humanitarian operation hubs in Africa with different levels of technological maturity, providing valuable comparative insights. Second, these countries face recurring humanitarian challenges that would benefit from enhanced supply chain resilience through AI-BDA adoption.

The research scope is limited to four key AI-BDA techniques in HSCs: Time-Series Forecasting (TSF), Early Warning Systems (EWS), Logistics Optimization (LO), Real-time Monitoring (RTM). This focused approach is justified as these techniques represent the most prevalent and impactful applications of AI-BDA in humanitarian contexts, as identified in current literature (Dubey et al., 2021; Hasan et al., 2023).

The study's participant scope encompasses 200 professionals from humanitarian organizations, including supply chain managers, data scientists, IT specialists, and operational leaders. This diverse professional sample is justified as it provides comprehensive insights from both technical and operational perspectives.

The scope deliberately excludes detailed technical specifications of AI algorithms and instead focuses on practical implementation and effectiveness, as this aligns with the study's aim of providing actionable insights for humanitarian organizations seeking to enhance their supply chain resilience through AI-BDA adoption.

1.9 Organisation of Thesis

This thesis is structurally organised into six substantive chapters that fulfil specific roles in addressing the research objectives and offering a complete examination of AI-BDA integration in humanitarian supply chains.

Chapter One: Introduction sets the framework of the whole study by introducing the research background, providing context for the importance of AI-BDA technologies in humanitarian operations in the context of rising global crises. The chapter presents the problem statement that defines the gap between the theoretical potential of AI-BDA and its actual use in humanitarian practice. It specifies the purpose of the study and a specific set of objectives, establishes research questions that direct the research, and states testable hypotheses. The chapter further discusses the importance and relevance of the study to the body of academic knowledge and humanitarian practices. It describes the methodology of the research conducted, outlines the scope and limitations of the research, and concludes with the organisation of the thesis.

Chapter Two: Literature Review provides a thorough synthesis of existing knowledge by reviewing related literature of AI-BDA applications in humanitarian operations. The chapter also examines theoretical underpinnings, such as a significant discussion of humanitarian supply chain resilience, AI practices, and big-data analysis in crises. It introduces three theoretical frameworks - Socio-Technical Systems Theory, Resource-Based View Theory, and Resilience Theory - on which the study builds its analysis. The empirical review analyses past research on AI-BDA effects, barriers to implementation, and literature gaps that warrant the present study.

Chapter Three Methodology describes the research methodology and implementation plan. It outlines the positivistic research paradigm embraced, the deductive nature of conducting theory testing, and rationalises the quantitative methodological preference employed. The chapter defines the study population, sampling methods, and data collection process, the conceptual framework between variables, measurement scale and its validation, measures of validity and reliability, methods of data analysis, and ethical considerations throughout the research process.

Chapter Four: Results and Analysis presents comprehensive findings from the empirical investigation. It begins with response rates and demographic profiles, conducts measurement validation through reliability and validity tests, addresses each research objective systematically through exploratory factor analysis and descriptive statistics for AI-BDA techniques, employs regression analysis to examine effects on supply chain resilience, identifies and ranks implementation barriers, and discusses findings in relation to existing literature and theoretical frameworks.

Chapter Five: Discussion critically interprets the findings by comparing findings with other precedent studies, analysing implications through the theoretical lens, examining both positive and negative implicatios of AI-BDA implementation, discussing practical and theoretical contributions, addressing limitations, potential biases, and synthesising the findings in advancing the knowledge base of AI-BDA in humanitarian situations.

Chapter Six: Conclusions and Recommendations sums up the critical findings of the study, provides evidence-based recommendations to practitioners and policymakers, outlines the limitations of the study, and offers future research directions on the topic of integrating technology into humanitarian supply chain management.

1.10 Conclusion

Applying AI-BDA in HSCs can potentially improve the efficiency and effectiveness of disaster response and relief. The frequency and severity of global crises have increased; hence, there is a greater need for effective solutions in humanitarian operations. This chapter has provided a basis for discussing how AI-BDA can improve the HSCOs to be more proactive and predictive instead of reactive.

The background information offered a brief on the humanitarian sector, the principles that govern it, and the challenges around humanitarian logistics and supply chains. It depicted the challenges of traditional HSCs and how AI and BDA can help solve these problems. The problem statement highlighted the gaps in the existing research, such as the absence of practical application studies and the fragmented literature on AI-BDA in humanitarian settings.

This research intends to close the gap between the theoretical potential of AI-BDA and its actual application in the humanitarian supply chain. This paper aims to come up with findings from the assessment of the existing applications, the effectiveness of these applications, the challenges faced and recommendations that may be useful to the academic world and the practical aspects of humanitarian operations.

This research implies that it can transform humanitarian operations and make them more robust and adaptive to the challenges of contemporary world crises. Thus, the results of this study will be helpful in decision-making, help predict further steps in the integration of technologies in humanitarian organisations and contribute to improving disaster response. The following chapter provides a detailed analysis of the existing empirical studies and theoretical frameworks used to guide this study.

CHAPTER TWO

LITERATURE REVIEW

2.0 Introduction

This literature review synthesizes the theoretical underpinnings, concepts, and empirical evidence on incorporating AI-BDA in Humanitarian Supply Chain Operations (HSCO) with an emphasis on supply chain resilience. The review commences with a comprehensive exploration of three fundamental theoretical paradigms foundational to the discussion. Socio-Technical Systems Theory, Resource-Based View Theory and Resilience Theory. Combining these theories is essential in explaining the interaction between technological advancement and organizational systems, the role of resources in establishing competitive advantage, and enhancing an effective and efficient supply chain in humanitarian crises.

The conceptual review section defines and describes AI and BDA solutions and delineates their specifications and consequent operative repercussions within humanitarian supply chain management. This section also defines HSCR and outlines key factors and measures to enhance system resilience. The review primarily focuses on how emerging technologies can improve the supply chain and disaster response outcomes. The empirical review section presents recently published studies about the effects of AI-BDA integration on HSCR and its associated challenges and barriers. Lastly, the summary of the literature review is presented.

2.1 Conceptual Review

2.1.1 Humanitarian Supply Chain Resilience

Humanitarian supply chain resilience (HSCR) is a significant concept in disaster response and relief activities, representing a fundamentally different orientation than classic supply chain management. HSCR is understood as the ability of humanitarian actors to prevent, prepare for, absorb, and recover from disruption while maintaining key life-saving delivery mechanisms

(Ali et al., 2017; Singh et al., 2018). Given the growing nature, impact, and complexity of disasters in the modern world, HSCR has become vital to sustaining human lives, providing effective aid, and preserving human life for various vulnerable populations (Tatham et al., 2009; Lewin et al., 2018).

HSCR is fundamentally different from commercial supply chain resilience in several key ways, which speaks volumes about the humanitarian context. Commercial supply chains are primarily concerned with profit maximisation, cost-effectiveness, and certainty in market demands. HScs are motivated to provide life-saving aid (Stewart & Ivanov, 2022; Chowdhury & Quaddus, 2016) to prevent and/or alleviate human suffering in unpredictable and highly volatile circumstances.

The donor-beneficiary relationship in humanitarian contexts gives rise to a unique triadic framework that is distinct from that in commercial contexts. For instance, commercial supply chains involve direct transactions with customers who utilise their purchasing power. In contrast, humanitarian beneficiaries neither transact as consumers nor have real purchasing power over the goods and services they receive (Oloruntoba & Grey, 2006). HSCs must also balance the 'customer service' aspect between both aid beneficiaries and their donors simultaneously and therefore have to manage complex accountability mechanisms, which commercial supply chains do not encounter (Bhattacharya et al., 2014).

Moreover, HSCs face unique operational challenges and constraints that traditional commercial supply chains do not face, such as asymmetric and unpredictable funding cycles, donations restricted to specific purposes from donors (and subsequently limited operational flexibility), and the operational structure and coordination of multiple organisations with differing mandates (Burnard et al., 2018). These organisations lack a clearly defined hierarchy, which means HSCs operate with less defined avenues to resilience as well as in an unstandardized and decentralised manner compared to commercial supply chains that operate in standardised and integrated frameworks (Scholten et al. 2014).

2.1.2.1 Specificities of HSCR

The term HSCR encompasses more than the conventional usages of robustness or shock absorption capacity; Rather, HSCR connotes an organisation's dynamic capacity that humanitarian organisations can continually utilise to act within their operating environments through organisational learning and agile development (Behl & Dutta, 2019). These dynamic capabilities are particularly important when considering the fact that humanitarian operations take place in dynamic, unpredictable environments characterised by damaged infrastructure, security threats, and severe resource constraints – conditions often not experienced in commercial environments.

HSCR embodies a few unique characteristics that set it apart from commercial resilience approaches. First, HSCR involves urgency imperatives, where consequences of delays can lead to loss of life rather than just financial costs (Altay et al., 2018). Second, HSCR requires multi-stakeholder coordination across different organisations such as the UN, NGOs, government organisations, and the private sector, where each organisation has different aims and operating procedures (Jahre & Fabbe-Costes, 2015). Finally, HSCR must operate in a resource-constrained environment where funding uncertainty and donor requirements heavily limit operational flexibility (Nurmala et al., 2017).

An excellent example of HSCR's adaptive capacity was evident during the COVID-19 pandemic, illustrating how humanitarian organisations effectively adapted their operations to respond to unprecedented global challenges while maintaining vital services (Ivanov & Dolgui, 2020). This demonstrates the essential principle of HSCs, which is that their design cannot simply be about returning to a state prior to disruption, but instead evolving and upgrading HSC capacity to better serve populations in need.

HSCR also embraces localisation principles by recognising that sustainable humanitarian response encompasses building local capacity and engaging local actors, which ultimately provides greater long-term resilience (Stumpf et al., 2023). This represents a measure of the fundamental difference between humanitarian organisations that focus on sustaining local supply chain capacity over the long term versus creating dependency on external sources, compared to commercial supply chain objectives.

2.1.2.1 Identification of Criteria and Indicators

Prior studies reviewed in this paper have outlined the multiple factors in developing resilience in HSCs. It has been established due to pre-assessment (Agarwal et al., 2020), various stakeholders (Venkatesh et al., 2019), strategic management (Behl & Dutta, 2019), responsiveness (Fathalikhani et al., 2020), risk management (Petrudi et al., 2020), and material support (Zhang et al., 2019).

Need assessment is the process of rapidly identifying the needs of the disaster-affected area and the capacity of the humanitarian supply chain. It is very crucial in the humanitarian supply chain. As Nagurney and Qiang (2019) highlighted, demand identification is an essential preliminary step in commercial and HSCs. However, the need for HSCs in a disaster is unpredictable and dynamic. This matter calls for humanitarian SCM to make a priori estimation of the requirements, for instance, through risk assessment models and information dissemination (Kunz & Gold, 2017). Another crucial aspect is the analysis of the transportation links that form part of the humanitarian supply chain pre-assessment (Munyaka & Yadavalli, 2021). For instance, using drones to gather data on transportation links has been crucial in reducing rescue time (Azmat & Kummer, 2020). Furthermore, the pre-assessment of resources also benefits the humanitarian SC's resilience, as noted in previous works (Prasad et al., 2018). In their study, Chen et al. (2020) suggested that resource sharing enhances the sustainability of the humanitarian supply chain.

Humanitarian supply chain stakeholders comprise governmental departments, enterprises, humanitarian agencies, and volunteers (Nagurney & Qiang, 2019). In his case, Dubey et al. (2020a) provided a detailed insight into British Telecom's disaster relief operations scenario. It was revealed that transparency within the humanitarian supply chain improves its robustness. Reference was also made to the fact that the integration of actors and the formation of trust among them within a short period benefits the CSHSC (Dubey et al., 2020a). In another study, it was clear that HSCs' problems stem from a need for more trust and collaboration (Dubey et al., 2020b). John et al. (2019) investigated the humanitarian supply chain in the Chennai flood case and indicated that information exchange equals coordination.

Strategic management is thus sensitive to the management team's capacity, including planning, timely inspection of efficiency and quality, and timely and efficient logistics management (Behl & Dutta, 2019). Torabi et al. (2018) argued that strategic planning is the foundation for making the right decisions. According to L'Hermitte et al. (2017), sustainable strategic management requires an overall strategy and new choices in the light of phased disasters. According to John & Ramesh (2012), humanitarian supply chain managers should verify the origin of the supplies and conduct adequate examination of the donated commodities. A paper by Nayak and Choudhary (2022) highlighted the role of an expansive streamlining model in a humanitarian supply chain. The study's results confirmed this notion and pointed out that the effectiveness of the HSCs can only be achieved with accurate logistics.

Responsiveness is one of the main characteristics of the technical component of the humanitarian supply chain and encompasses procedural flexibility, management adaptability, and procedural velocity (Stewart & Ivanov, 2022). Specifically, the cross-sectional study of Dubey et al. (2021) showed that using technological tools contributes to the increased flexibility of HSCs. They also pointed out that disaster relief actions are more efficiently dealt with when the humanitarian supply chain is strategic and sensitive. This implies the need to apply adaptive management strategies because floods often occur unexpectedly and have unpredicted impacts (Schiffling et al., 2020). Charles et al. (2016) noted that it is evident that shorter unnecessary pipeline time causes a positive effect towards the efficiency of the humanitarian supply chain. It was also suggested that the policy of pre-assessment is beneficial for forming the conditions that contribute to faster decision-making.

Due to the complexities and uncertainties involved in the humanitarian supply chain during flood events, effective risk management is key to improving resilience. Risk management includes warning capability, risk awareness, and distributed power (Jahre, 2017). The capability of risk warning is essential to the primary setup of the humanitarian supply chain. Not only does this ability enhance the effectiveness of the supply chain, but it also reduces and eliminates the wastage of resources (Stauffer & Kumar, 2021). Thus, Patil et al. (2021) conclude that the need for risk awareness is one of the critical challenges to the sustainable management of HSCs. The cultivation of risk awareness should involve at least two significant bodies that is (i) rescuers and first responders, and secondly (ii) community members (Patil et al., 2021). Due to frequent interruptions of information exchange in flood events, it becomes essential to incorporate distributed power (Prasad et al., 2018).

However, it is only possible to strengthen the humanitarian supply chain's resistance with substantial supply and contribution, such as big data, the qualified workforce, and standardization (Behl & Dutta, 2019; Papadopoulos et al., 2017). According to Oscar's research results, AI can significantly increase the resilience of HSCs (Rodríguez-Espíndola et al., 2020). de Camargo Fiorini et al. (2022) highlighted that an efficient humanitarian supply chain cannot be considered without efficient human resource management Based on the literature review conducted by Ismail, the author noted that standardization could elevate substitutability regarding the materials used and strengthen the overall humanitarian SCM (Ismail, 2021).

2.1.2 Review of AI in HSCs

AI is an umbrella term that covers a vast area of study, including machine intelligence, robotics, and computational vision (Aggarwal & Yu, 2021). The main goal is to mimic human cognition processes in realizing decision-making, textual analysis, and image understanding (Aggarwal & Yu, 2021; Harish et al., 2023). AI is popular because people dream of creating a new, superior society (Manyika, 2022).

AI is already making a positive impact across multiple industries. Using this technology in the humanitarian supply chain is an innovative step forward in solving numerous issues that arose during crises and their management. Regarding humanitarian supply chain management, one of the most important uses of AI is in the needs assessment or demand forecasting. It can be challenging, especially for traditional approaches, due to the dynamism and unpredictability of humanitarian crises (Jha, 2024; Kreutzer et al., 2019). AI algorithms, such as machine learning, can help forecast resource demand by processing data from satellite imagery, social media, and historical data (Kumar et al., 2024). For instance, Rodríguez-Espíndola et al. (2020) have shown the integration of blockchain and 3D printing systems that can enhance demand forecasting and resource allocation in a disaster management context.

AI is also used effectively to improve logistics and transportation of products in the humanitarian supply chain. These routing algorithms can also consider factors like roads, security risks, and urgency of delivery to identify the best routes to use (Zabinsky et al., 2021; Yousefzadeh, 2020; Alturki & Lee, 2024). Alçada-Almeida et al. (2022) proposed a methodology for post-disaster response that minimized the delivery time of humanitarian aid products (including medicines, water and food) from the temporary depots to demand points and meet the needs of the affected public.

Another crucial use is in inventory control and resource customization. AI systems can easily control inventory using real-time information, ensuring that essential stocks are available in specific areas when needed (Kumar et al., 2024; Preil & Krapp, 2021). AI also helps improve cooperation and collaboration between various agencies or entities involved in humanitarian interventions (Fan et al., 2021). It fosters the use of multiple data streams and improves resource utility and information quality (Devitt et al., 2021). Other forms of AI, such as chatbots, present an avenue for enhanced interaction with affected communities, although there are concerns over data protection and possible signal disconnect (Madianou, 2021).

However, some challenges are coupled with the incorporation of AI within the humanitarian supply chain. Some problems include the security risks of cyber-attacks, the absence of adequate infrastructures (Nozari et al., 2022), privacy challenges, and the algorithms' transparency (Ejjami & Boussalham, 2024). To address such issues, scholars propose the following solutions: strengthening continual comprehensive frameworks in AI management, establishing executive positions solely for AI supervision, and assessing the performance of AI on the humanitarian supply chain over a long period (Ejjami & Boussalham, 2024; Smyth et al., 2021).

2.1.3 Review of BDA in HSCs

A novel area of research that has shown great potential in humanitarian operations is BDA, which can significantly improve the strategic and tactical performance of reconstructed supply chains in disaster relief contexts (Dubey et al., 2018; Dennehy et al., 2021). The use of BDA in humanitarian settings is thus motivated by the rising sophistication and incidences of emergencies across the globe and the rapid expansion of data collection from multiple sources and formats (Dubey et al., 2021). The combination of technology with humanitarian causes will likely change the face of aid delivery in the future.

Essentially, BDA in HSCs entails accumulating an enormous amount of data from multiple sources and analyzing it to make informed decisions and improve the flow of business (Gupta et al., 2017; Prasad et al., 2016). Some potential data types may comprise satellite images, social media feeds, sensors, archival data on disasters, and others (Papadopoulos et al., 2017). When utilizing this immense stock of information, humanitarian organizations can obtain specific up-to-the-minute details about ongoing calamities and determine the probable future requirements to provide requisite aid much more efficiently.

It has been found that one of the prevalent uses of BDA in supply chains of humanitarian organizations is demand forecasting and needs assessment (Sahebi & Jafarnejad, 2018). Currently, need assessments in disaster-stricken communities are usually done through cumbersome paper-and-pencil surveys and reports (Chan, 2006; Korteweg et al., 2010). However, BDA provides the capability to analyze multiple data streams simultaneously for a more integrated and real-time understanding of the situation on the ground (Ragini et al., 2018; Swaminathan, 2018). For example, Makker et al. (2019) show how BDA is applied to identify issues on social media and satellite imagery to determine loss and rapidly prioritize intervention after a disaster.

Another essential domain for which BDA is highly efficient is inventory control and supply chain management (Maheshwari et al., 2020). Non-governmental organizations involved in humanitarian logistics are constantly faced with the complex task of storing resources in advance to avoid the risks of deliveries during disasters while being ready to respond to other incidents and emergencies. It can assist by using BDA to look into records, current trends, and various models that aid stockpiling and distribution (Mathrani & Lai, 2021; Aljabhan & Abeyie, 2022). It may also be beneficial regarding resource utilization and response time to crises since it is based on data.

Transportation and logistics planning is yet another domain in which BDA is proving extremely useful. With the help of real-time data, including road conditions, weather patterns, and the movements of populations, human organizations can plan their supply lines and delivery networks more effectively (Warnier et al., 2020). Li & Lv (2021) highlight that in BDA, dynamic routing can be utilized to create algorithms that can cover the changes in the ground and ensure that the help gets to the destination using the most suitable and safest way possible.

However, using BDA in HSCs is challenging, even though it can positively impact them. Some challenges, such as data quality challenges, privacy questions, and the necessity of having specialized technical skills, may act as limitations to adoption (Jain et al., 2023). However, it is noteworthy that due to the unpredictable and frequently emotionally tense atmosphere of disasters, data collection and analysis can be carried out irregularly (Spence & Lachlan, 2010; Morton & Levy, 2011). These challenges can only be addressed by collaborating with humanitarian organizations, technology companies, and policymakers to formulate efficient, moral, and viable BDA solutions suitable for humanitarian missions. Finally, considering future development, there is potential to incorporate BDA with other developing technologies like AI and the Internet of Things (IoT) to augment HSCs. Technologies like these can enhance the flexibility, robustness, and effectiveness within the supply chain domain (Zamani et al., 2022; Dubey et al., 2020).

2.1.4 Justification for AI-BDA Integration over Alternative Technologies

The integration of AI and BDA in HSCs represents a strategically synergistic approach that addresses the unique complexities and data-intensive nature of humanitarian operations. AI and BDA form a complementary technological ecosystem where BDA provides the foundation for processing vast, heterogeneous datasets generated during humanitarian crises, while AI transforms this data into actionable intelligence (Zamani et al., 2022). BDA's capability to handle the "four Vs" of big data: volume, velocity, variety, and veracity enables humanitarian organizations to process satellite imagery, social media feeds, sensor data, and historical disaster records simultaneously (Dennehy et al., 2021). AI algorithms then apply machine learning, natural language processing, and predictive analytics to extract meaningful patterns and generate forecasts that are critical for humanitarian decision-making (Dubey et al., 2022).

This synergy is particularly crucial in humanitarian contexts where organizations must rapidly process information from multiple sources to make life-saving decisions. For instance, AI-powered early warning systems can analyze weather patterns, geological data, and social media sentiment processed through BDA to predict disaster impacts with 86.7% accuracy (Tomas et al., 2022). Such precision is unattainable through individual technologies operating in isolation.

The humanitarian supply chain environment presents unique challenges that require sophisticated technological solutions. Unlike commercial supply chains, humanitarian operations face unpredictable demand patterns, disrupted infrastructure, and the need for rapid response in resource-constrained environments (Rodríguez-Espíndola et al., 2020). AI-BDA integration addresses these complexities through predictive analytics that forecast demand fluctuations and optimize resource allocation in real-time.

Research demonstrates that AI-BDA applications in humanitarian contexts can reduce logistics costs by 15%, improve inventory levels by 35%, and enhance service levels by 65% (World Economic Forum, 2025). These improvements are achieved through AI's ability to process BDA-generated insights to optimize routing algorithms, predict supply chain disruptions, and automate response mechanisms.

The AI-BDA integration offers a more comprehensive approach to supply chain resilience by addressing all four phases of resilience: readiness, response, recovery, and adaptability (Zamani et al., 2022). This holistic approach enables humanitarian organizations to transition from reactive to proactive operations, utilizing predictive analytics to anticipate disruptions and optimize resource deployment before crises occur.

The technological convergence also facilitates enhanced coordination among multiple humanitarian stakeholders through shared data platforms and AI-powered decision support systems. This collaborative capability is essential in humanitarian contexts where effective coordination between government agencies, NGOs, and international organizations can significantly impact response effectiveness (Dennehy et al., 2021).

2.1.5 Review of Existing techniques of AI-BDA in HSC

2.1.5.1 Time-Series Forecasting (TSF)

Time-Series Forecasting (TSF) represents a critical application of AI-BDA in HSCs, enabling organizations to predict and prepare for future demands and disruptions. This technique leverages historical data patterns to generate predictions that support proactive decision-making in humanitarian operations (Chan et al., 2015; Kumar et al., 2012). The implementation of TSF has become increasingly sophisticated with the integration of advanced AI algorithms and machine learning methods.

Fuzzy time series analysis has emerged as a particularly effective method for managing disrupted supply chains, as it can handle the uncertainty and complexity inherent in humanitarian operations (Chan et al., 2015). This approach is especially valuable when dealing with imprecise or incomplete data, which is common in crisis situations. Case-based reasoning systems have also proven effective for emergency resource demand prediction, learning from past humanitarian responses to inform future operations (Sahebi & Jafarnejad, 2018).

In the context of medical supply management, SARIMA models have demonstrated significant utility in inventory forecasting, accounting for both seasonal variations and long-term trends in demand patterns (Shah et al., 2023). This is particularly crucial for humanitarian organizations managing medical supplies with limited shelf lives and specific storage requirements.

Recent advances have introduced more sophisticated approaches, such as the integration of robust principal components analysis with extended short-term memory networks. This combination has shown promising results in forecasting commodity-specific demands in humanitarian contexts (Fuqua & Hespeler, 2022). Additionally, probability distribution-based tools have enhanced the accuracy of natural disaster prediction, enabling better preparation and resource allocation (Kumar et al., 2012).

The implementation of deep learning algorithms has further revolutionized time series forecasting in HSCs. These methods can process vast amounts of historical data to identify complex patterns and relationships that might be missed by traditional statistical approaches (Ali et al., 2024). For instance, neural networks have been successfully employed to predict post-disaster resource requirements with higher accuracy than conventional methods (Belhadi et al., 2024).

Modern TSF techniques also incorporate real-time data streams and external factors such as weather patterns, population movements, and social media signals to enhance forecast accuracy. This multi-dimensional approach to forecasting helps humanitarian organizations develop more robust and adaptable supply chain strategies (Dennehy et al., 2021).

2.1.5.2 Early Warning Systems (EWS)

Early Warning Systems (EWS) represent a crucial advancement in humanitarian supply chain management, leveraging AI and machine learning algorithms to predict and prepare for potential disasters. These systems have evolved from simple monitoring tools to sophisticated predictive platforms that enable proactive disaster response and resource deployment (Hasan et al., 2023).

Machine learning algorithms, particularly Random Forest and Gradient Boosting, have demonstrated remarkable accuracy in disaster prediction. For instance, these algorithms achieve accuracy rates of 86.7% in flood susceptibility prediction and 80% in flood risk classification (Tomas et al., 2022). This high level of accuracy enables humanitarian organizations to mobilize resources and position supplies strategically before disasters strike, significantly improving response effectiveness.

Recent developments in Early Warning Systems (EWS) have incorporated multi-source data integration to enhance prediction capabilities. These systems combine satellite imagery, weather patterns, geological sensors, and social media data (Phengsuwan et al., 2019; Shoyama et al., 2020). The integration of social media into EWS has improved public response monitoring and local flood detection (Kitazawa & Hale, 2020; Shoyama et al., 2020). This comprehensive approach allows for more nuanced and context-aware predictions, particularly in regions prone to multiple types of natural disasters.

Recent research demonstrates the effectiveness of deep learning models in enhancing Early Warning Systems (EWS) for various disasters. Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks have shown particular promise in earthquake detection and parameter estimation (Zhang & Zhang, 2023; Carratù et al., 2022), improving accuracy and response times compared to traditional methods. Similar approaches have been applied to hydrological forecasting (de la Fuente et al., 2019) and flash flood prediction (Panahi et al., 2020; Lima & Scofield, 2021), yielding more accurate and timely warnings.

The integration of IoT technologies with Early Warning Systems (EWS) has significantly enhanced disaster monitoring and prediction capabilities. IoT-based EWS provide real-time data collection, improved sensor connectivity, and automated alert systems for various natural hazards, including floods, earthquakes, and landslides (Segalini et al., 2020; Esposito et al., 2022). These systems utilize wireless sensor networks, cloud computing, and machine learning algorithms to process data and generate timely warnings (Siddique et al., 2023; Zambrano et al., 2017). The incorporation of virtual sensors and hydrological simulation models further improves forecast accuracy and extends warning times (Nanni & Mazzini, 2018). IoT-based EWS also enhance semantic interoperability, allowing for better integration of diverse data sources and more effective emergency response (Moreira et al., 2018).

Modern Early Warning Systems (EWS) incorporate predictive analytics to optimize supply chain resilience and enable proactive resource allocation based on disaster probability assessments. These systems integrate advanced technologies like AI and virtualization to improve risk identification and model complex supply chains (Gillespie, 2023).

2.1.5.3 Logistics Optimization (LO)

Logistics Optimization (LO) represents a critical application of AI-BDA in HSCs, where advanced algorithms are deployed to enhance operational efficiency and reduce costs while maintaining effective emergency response capabilities. AI algorithms have demonstrated significant improvements in delivery processes, making them both more effective and cost-efficient in humanitarian contexts (Abhulimen & Ejike, 2024).

The implementation of multi-criteria decision-making models and heuristic solutions has revolutionized the way humanitarian organizations manage resource movement during emergencies (Ortuño et al., 2021). These sophisticated optimization models consider multiple objectives simultaneously, including minimizing response time, maximizing coverage, and optimizing resource utilization. For instance, vehicle routing optimization algorithms have shown particular promise in improving last-mile delivery efficiency in disaster-affected areas.

Evidence-based optimization approaches have proven invaluable in informing policy decisions and operational strategies in humanitarian work (deVries, 2017). These approaches leverage historical data and real-time information to develop dynamic routing solutions that can adapt to changing conditions on the ground. Klundert et al. (2013) demonstrate how such optimization techniques can significantly improve the efficiency of medical supply distribution in crises.

The integration of mobile technology has further enhanced logistics optimization capabilities by enabling real-time tracking and decision-making. Li et al. (2015) highlight how mobile platforms facilitate the development of multi-objective decision-making models that effectively balance economic and social costs. These models help decision-makers optimize resource allocation while considering both operational efficiency and humanitarian impact (Serrato-Garcia et al., 2016).

Recent advances in machine learning have led to more sophisticated optimization algorithms that can handle the complexity and uncertainty inherent in humanitarian operations. For example, recent research demonstrates the successful application of reinforcement learning (RL) algorithms to dynamic vehicle routing problems (VRPs). RL-based approaches have shown competitive or superior performance compared to traditional methods, especially for complex VRP scenarios (Ara et al., 2023; Zhou et al., 2023).

The implementation of digital twins in humanitarian logistics has also emerged as a powerful tool for optimization. Digital twins have emerged as powerful tools for optimization in logistics, including HSCs. They enable real-time decision support, flexible responses, and operational control based on current data (Zuhr et al., 2022; Bányai, 2022). Digital twins integrate various technologies like IoT, cloud computing, and simulation-based optimization to improve logistics processes (Marić et al., 2021; Matyi & Tamás, 2021).

2.1.5.4 Real-time Monitoring (RTM)

Real-time Monitoring (RTM) has emerged as a crucial AI-BDA application in HSCs, enabling organizations to track resources and respond swiftly to dynamic situations. AI-powered monitoring systems significantly enhance responsiveness in unstable environments by providing continuous visibility of stock levels and resource movements (Abhulimen & Ejike, 2024; Gupta et al., 2019).

The development of sophisticated logistics management monitoring systems has addressed critical challenges in HSCs, particularly regarding data collection, control mechanisms, and information display in remote and challenging environments (Salvadó et al., 2016). These systems provide real-time visibility of essential resources, including relief goods, equipment, and personnel locations (Yang et al., 2011), enabling more effective coordination and resource allocation.

The integration of dynamic in-field data has revolutionized decision-making processes in disaster response scenarios (Yagci Sokat et al., 2016). Modern RTM systems leverage multiple technologies, including RFID and Wi-Fi, to enable precise location tracking during humanitarian crises (Budak et al., 2020). These technologies have proven particularly valuable in complex emergency environments where traditional tracking methods may be unreliable.

Recent advances in IoT sensors and edge computing have further enhanced RTM capabilities in humanitarian operations. These technologies enable efficient data collection, processing, and analysis at the edge, reducing latency and improving decision-making speed in time-critical situations (Rossetti et al., 2022; Pathinarupothi et al., 2019). For instance, smart container solutions equipped with environmental sensors can monitor temperature-sensitive medical supplies throughout the supply chain, ensuring their integrity during transport and storage (Salah et al., 2020; Raman et al., 2023).

The implementation of blockchain technology in RTM systems has improved data transparency and traceability in HSCs (Martinez & Wilson, 2024). Studies have identified key drivers for blockchain adoption, including accountability, visibility, and trust (Baharmand et al., 2021). The technology can improve swift-trust, collaboration, and resilience among humanitarian actors (Dubey et al., 2020). Furthermore, AI-powered predictive analytics applied to real-time monitoring data enable early detection of potential supply chain disruptions and automated response triggers (Aljohani, 2023; Rauf et al., 2024).

2.2 Theoretical framework

This section discusses the appropriate theories underpinning the study, which revolves around integrating AI-BDA in the HSCO. To address the integration of AI-BDA in HSCs, this study builds on three existing theories: Socio-Technical Systems Theory, Resource-Based View (RBV) Theory and Resilience Theory, as outlined below.

2.2.1 Socio-Technical Systems Theory

Trist and Bamforth formulated the socio-technical Systems (STS) Theory in the 1950s. It has become essential to conceptualizing intricate organizational systems, especially when technology is involved (Trist & Bamforth, 1951). This theory holds that productivity and efficacy within an organization, or a system depend on the integration and cooperation between the social aspects of a system – people and processes – and the technical aspects – technology and tools (Baxter & Sommerville, 2011).

The central focus of STS Theory is that optimal system performance can only be achieved when social and technical elements are planned to form an integrated whole. Therefore, it presents a more realistic view of the belief that deploying technology is a panacea to organizational ills by admitting that technology interventions cannot work in isolation but must be complemented by human intervention and organizational structures supporting these technological solutions (Clegg, 2000). The theory comprises several principles, including joint optimization, where social and technical systems are optimized together rather than individually (Eason, 2014). In addition, it stresses the dynamic nature of the organization and states that systems should be able to accommodate such dynamics, meaning they should be adaptable (Davis et al., 2014). Additionally, STS Theory stresses the importance of human values, where human values and needs should be considered when designing the system (Cherns, 1976).

In the recent past, STS Theory has been used in different areas such as information systems, healthcare, and supply chain. This has mainly been so given the rise of novel, sophisticated technologies like AI and the BDA. According to Sarker et al. (2019), both AI and BDA should be integrated into organizations' processes and, therefore, call for a socio-technical perspective for their integration. This is especially important in HSCs, where technology support must be compatible with human performance, organizational strategies, and objectives.

The use of STS Theory in HSCs has essential implications for the following reasons. First, humanitarian actions are characterized by their multifaceted nature regarding the involvement of various actors, cultural sensitivity, and rapidly changing environments. An STS approach helps address such complications (Jahre et al., 2015). Secondly, due to the growing use of AI and BDA in humanitarian operations, STS theory is beneficial in helping not to disrupt but to support the current social structure and functioning in such organizations (Comes, 2016). Finally, yet importantly, since humanitarian work is essential and the risk of saving lives can be much higher than the risk of carrying out a dangerous mission, it is vital to apply technology-based solutions with a deep understanding of the user needs and capabilities. STS Theory supports this humanistic perspective emphatically (Holguín-Veras et al., 2012).

Recent research has revealed the value of applying STS Theory in humanitarian situations. Quarshie et al. (2019) employed an STS approach to analyze the factors hindering sustainable supply chain management integration into humanitarian operations. They discovered that organizational culture and technology need to be intertwined to make effective implementation. In another study, to understand the impact of BDA on supply chain resilience during COVID-19, Dubey et al. (2020) used STS Theory. They agree that while people have shown that the technology is robust, they equally consider the human aspect in developing resilient systems. Additionally, Gupta et al. (2021) employed the STS approach to assess the adoption of blockchain technology in the humanitarian supply chain. They also determined specific socio-technical requirements that define the implementation of the system; these are the organizational readiness and the willingness of the users to accept the new system.

The use of Socio-Technical Systems Theory in analyzing AI and BDA in HSCs is justified for several reasons. First, it offers a theoretical foundation for understanding technological solutions for implementing AI-BDA in humanitarian missions and their social aspects. This aligns with the aim of identifying and evaluating specific applications of AI and BDA in enhancing supply chain resilience. STS Theory enables analyzing the challenges connected with the application of AI-BDA in HSCs, which contributes to achieving the objective mentioned above by recognizing potential social and technical barriers.

2.2.2 Resource-Based View (RBV) Theory

The Resource-Based View (RBV) theory that Wernerfelt (1984) put forth and Barney (1991) later developed has been viewed as one of the most critical theories within the field of strategic management and organizational research. This theory assumes that competitive advantage is rooted within a firm's ownership-specific resources, whereas the resource position depends on the firm's market position (Barney, 1991). The RBV focuses on internal resources and capabilities that can enable an organization to gain and sustain a competitive advantage, given the fact that a resource is valuable, inimitable, rare and non-substitutable (Barney, 1991; Kraaijenbrink et al., 2010).

Other views that have emerged over the years include dynamic capabilities (Teece et al., 1997), knowledge-based view (Grant, 1996) and natural resource-based view (Hart, 1995). These extensions have expanded the areas of the theory, such as supply chain management and information systems (Hitt et al., 2016; Wade & Hulland, 2004). This evolution has increased the applicability of the RBV among scholars, especially in emerging technologies where the impact on organizational performance is critical.

From the RBV perspective, the theory is relevant to discussing the humanitarian supply chain and application of AI and BDA technologies. Humanitarian organizations adapt to constantly changing contexts and work in a context that requires a strong mobilization and utilization of resources (Day, Demarest, and Snell, 2012). Therefore, AI and BDA are strategic resources that, unless applied or managed improperly, can benefit humanitarian organizations in a competitive environment (Dubey et al., 2019).

Some researchers have used the RBV to analyze the impact of technology on performance improvement in organizations operating in humanitarian organizations. For example, Rodríguez-Espíndola et al. (2020) employed the RBV to examine the role of BDA capabilities within disaster response systems. They discovered BDA capabilities for improving decision-making and operational efficiency in humanitarian response when other organizational resources exist. In the same way, Gupta et al. (2021) used the RBV to study how AI and machine learning technologies can improve supply chain robustness for humanitarian operations. According to their findings, when these technologies are seen as strategic resources, they assist organizations in gaining an appreciation and planning for disruption within the supply chain.

The RBV also offers a conceptual foundation for analyzing how organizations may build and sustain their AI and BDA competencies. Fosso Wamba et al. (2019) applied the RBV to test the BDA capabilities and their impact on the firm's performance. They identified evidence that firms that create new forms of BDA resources and capabilities can obtain better performance results. From the humanitarian perspective, RBV can help understand why such organizations are more efficient than others in applying AI and BDA in supply chain vulnerability reduction. Dubey et al. (2021) employed the RBV to examine the speed at which organizations can gain swift trust and increase collaboration within humanitarian supply chain networks utilizing blockchain solutions. Based on their insights, the authors state that blockchain can complement other organizational resources and capabilities to improve information exchange and cooperation between humanitarian stakeholders.

The use of RBV in approaching AI and BDA in humanitarian SCs is particularly appropriate for several reasons. First, it enables the researcher to examine AI and BDA as a strategic resource that may give humanitarian organizations a competitive advantage. This aligns with the intention to investigate the effects of innovative technologies, including AI and BDA, in improving supply chain resilience. Secondly, the theory offers guidance on how organizations can build and sustain their AI and BDA capabilities. Evaluating the extent to which these technologies support the strengthening of supply chain resilience in humanitarian crises is imperative.

Furthermore, by stressing the aspects of resource rarity and imitability, the RBV can aid in determining possible barriers to the application and integration of AI and BDA in Humanitarian SCs. This directly addresses the goal of assessing challenges in this area. The firm's theoretical framework RBV covers how resources enhance organizational performance to determine the impact of AI and BDA applications on improving the supply chain's resilience. Furthermore, the theory recognizes context as a critical factor in identifying the value of the resources. This is significantly true in humanitarian disaster types, whereby the disaster type, geographical region, and organizational cultures can influence the success of AI and BDA.

2.2.3 Resilience Theory

Resilience Theory has become a central paradigm for analyzing how systems, organizations, and people anticipate and manage disruptions. Kurtz and Snowden (2003) pointed out that the theory of resilience was initially coined and brought into the interdisciplinary sphere of study by Holling (1973); in the multidisciplinary field of ecology, it was later adopted by other discipline including psychology, engineering, and the more recent supply chain management field. Resilience can be broadly defined as the capacity of a system to tolerate disturbance, reorganize and endure while evolving (Walker et al., 2004).

Based on the analysis of the studies within the framework of organizational studies and supply chain management, resilience can be defined as a set of actions and measures that allow predicting potential failures, reacting to them, and bringing systems back to their usual mode of functioning (Ponomarov & Holcomb, 2009). This definition highlights three critical aspects of resilience: anticipation, adaptation, and recovery. With supply chain risks and complexities rising over the years and supply chains being heavily exposed to various risks, supply chain resilience has received more attention from researchers and practitioners (Kamalahmadi & Parast, 2016).

Resilience Theory has enabled the formulation of various frameworks and models relating to the supply chain. For example, Pettit et al. (2010) presented a framework where supply chain vulnerabilities are matched with capability gaps, indicating that supply chain resilience is the state of balance between the two. This framework further suggests that it is essential to pinpoint potential threats and acquire specific capacity to counter them.

In line with this argument, Wieland and Wallenburg (2013) advanced the idea of relational competencies as a critical component of improving supply chain resilience. They opine that these three elements are essential in developing resilience capabilities and are centred on communication, collaboration and interdependency between supply chain stakeholders. This perspective highlights resilience's social and relational aspects, moving beyond purely technical or operational considerations.

In recent years, the use of novel technologies, especially AI and BDA, has opened up new avenues for increasing the supply chain's resilience. Papadopoulos et al. (2017) specifically studied the application of big data in supply chain disruption management. They discovered that organizations possessing big data analytical capacity are more ready to prepare for disruption and response than recover effectively. In this regard, they posited that BDA could improve visibility throughout the entire supply chain and, subsequently, the level of risk management and decision-making.

Similarly, in another study, Dubey et al. (2021) explored the effects of AI on supply chain resilience. They found that AI capabilities can positively impact proactive and reactive resilience types. Their findings highlighted that AI could be applied to demand forecasting, real-time supply chain monitoring, and swift response to disruptions.

The use of Resilience Theory in the context of HSCs has its challenges and opportunities. This is especially the case when humanitarian operations are conducted in highly dynamic and unpredictable settings, which stresses the importance of factors contributing to operational resilience. According to Kovács and Tatham (2009), disaster situations are unique events that mean the humanitarian supply chain needs to be flexible, stressing agility.

In this context, both AI and BDA integration improvements into the humanitarian supply chain provide more capabilities for resilience. Rodríguez-Espíndola et al. (2020) identified the applicability of emergent technologies such as AI and BDA in humanitarian operations. They established that these technologies enhanced the accuracy of demand forecasting, resource allocation and the integration of supply chain actors.

Of the four premises of Resilience Theory, adaptive capacity is most important when discussing AI and BDA for HSCs. Adaptive capacity is defined as how flexible a system is in dealing with new circumstances (Folke et al., 2010). In the context of broader humanitarian operations, AI and BDA can strengthen adaptive capacity by delivering timely intelligence, supporting quick decision-making, and helping organizations learn from events.

Moreover, the multi-scalar nature of resilience, as emphasized by Resilience Theory, is crucial in the humanitarian context. Resilience should be conceptualized at individual, agency, and supply chain levels (Blackhurst et al., 2011). AI and BDA can strengthen resilience at the individual, organizational, and system levels through better planning, shared communication, and efficient resource management at the supply chain level.

To sum up, Resilience Theory is a solid foundation for analyzing and improving the specific characteristics of HSCs and their cooperation with AI-BDA. It focuses on anticipation, adaptation, and recovery, which correspond well with the issues encountered in humanitarian operations. The theory is most relevant to the current study of AI and BDA in HSCs in the following ways. Firstly, it offers a theoretical background on how these technologies can strengthen the resilience of organizations involved in humanitarian interventions, which answers the research question on the best uses for AI and BDA. Secondly, based on the concepts of adaptive capacity and multiple scales of analysis, Resilience Theory provides theoretical guidelines on the role of AI and BDA in enhancing decision-making and coordination at varying scales of operations. This is in line with the objectives of the study, which are to evaluate the effects of AI-BDA applications and examine challenges in implementation.

2.3 Empirical Review

2.3.1 Effects of AI-BDA on HSCR

Zouari et al. (2020) examined the relationship between Supply chain resilience (SCR) and Supply chain (SC) digitalization. A sample was considered with 300 professionals working in the field of SCM, and the data was evaluated through factor analysis and structural equation modelling (SEM). SEM was used to examine the moderating role of the degree of digital maturity and SC digital tools on SCR. They discovered that the conversion of the business supply chain, with help from BDA and AI, leads to visibility throughout the chain because such technologies help acquire essential information concerning the environment and the status of operating assets.

Building upon previous research, Belhadi et al. (2024) examined the mediation roles of supply chain resilience (SCRes) and supply chain performance (SCP) between AI and the dynamism and uncertainty of the supply chain context. Thus, they defined the use of AI in the supply chain with the help of the organizational information processing theory (OIPT). This research employed structural equation modelling (SEM) to assess the validity and reliability of the developed framework. Survey data was gathered from 279 firms of varying sizes across different industries and countries. The research affirmed the propositions of the framework under analysis by presenting the practical outcomes pointing at the significant impact of AI on SCP through the augmentation of the related metrics and fostering SCRes.

In a qualitative study, Modgil et al. (2022) highlighted how organizations use AI and how they think about AI to give visibility, risk, sourcing and distribution capacities to improve supply chain vulnerability. The authors collected high-quality data through purposive sampling and semi-structured interviews with 35 professionals associated with the e-commerce supply chain sector. The authors employed open, axial and selective coding approaches to systematically categorize the data and infer the elements that make AI-enabled supply chain resilience. The study's findings underscore five novel domains that can lead to improved and robust supply chain performance through the help of AI. Some of the key drivers for supply chain visibility are (1) transparency, (2) guaranteeing last-mile delivery, (3) delivering customized supply chain solutions to both upstream and downstream supply chain links, (4) managing the effects of disruption and (5) enabling a flexible procurement model.

According to Singh et al. (2024), robust evidence has been provided to determine the status of AI/BDA on supply chain resilience. To achieve the study's objective, the authors built the methodology to extract useful information from the literature studied and developed the Total Interpretive Structural Modelling (TISM) with the help of 44 supply chain professionals. The authors used a quantitative questionnaire and obtained 229 responses to test the model. With the analysis, a comprehensive and conceptual framework is developed. One of this study's significant findings is that supply chain analytics is requisite for supply chain resilience. The research findings support the hypothesis that the increased application of supply chain analytics has a positive and significant effect on the adaptability of demand forecasting to inventory management, enhancing the overall efficiency of supply chain networks.

A valuable study in this context has been provided by Bag et al. (2023), focusing on incorporating BDA in overcoming disruptions of supply chain systems in the COVID-19 process. The authors pointed out risks inherent in purchasing and supply chain management by establishing a hypothetical model to attain supply chain resilience through big data. The research team chose the samples from the automobile parts affiliated manufacturers' database in South Africa, which amounted to 375. The partial least squares structural equation modelling (PLS-SEM) technique was used to test the hypothetical model based on primary data from manufacturing industries. BDA tools could be effectively applied to restore and increase supply chain resilience.

2.3.2 Barriers to adopting and implementing AI-BDA within HSCs

In a comprehensive investigation by Raut et al. (2021) of Indian manufacturing Supply Chains, twelve crucial barriers that hinder the implementation of BDA were identified and evaluated. These barriers were constructed with an integrated two-phase methodology; in the first phase, Interpretive Structural Modelling (ISM) and Decision-Making Trial and Evaluation Laboratory (DEMATEL) were used in the second phase. The approach used here gives the pattern of the interactions between the given constructs and their relative intensities. Furthermore, the Fuzzy MICMAC technique considers the high impact (possessing high driving power) barriers in the context. The study findings reveal that four out of the ten constructs are the most critical barriers that affect the implementation of policies. They were as follows: Top management support, financial support, skills, and techniques/procedures.

In a significant contribution to the field, Dehkhodaei et al. (2023) sought to examine the challenges that Iranian organizations face in implementing BDA. Accordingly, 34 barriers to BDA adoption were identified in Iran based on a literature review and expert feedback. The most important barriers (14) were further classified, and their relationships were interpreted using integrated Interpretive Structural Modelling and MICMAC approach. Two barriers were highlighted in the study as most significant: the first is a significantly high level of insufficient knowledge of senior managers regarding the relevant issues, and the second is a significantly weak state of governance policies.

In another study, Kabra et al. (2023) set out to establish the challenges to information and digital technology (IDT) usage in organizations engaged in HSCs. To achieve this objective, the study adopted a literature review combined with consultant interviews and a fuzzy analytic hierarchy process (F-AHP) to find and rank all the barriers organizations implementing HSCs may consider to enhance IDT use. These barriers included the five main barriers: strategic, organizational, technological, financial, and human, interrelated with 25 sub-barriers that impacted the level of IDT Adoption in organizations involved in susceptible contracts. The results revealed that the most crucial categories are strategic barriers (SB) and organizational, technological, financial, and human barriers.

The Bag et al. (2022) study made considerable input to identify the barriers to BDA in sustainable humanitarian SCM. The data collection technique used in this study is the Fuzzy Total Interpretive Structural Modelling (TISM) approach. The results of the Fuzzy TISM model are statistically analyzed with the help of 108 responses collected from Africa-based humanitarian organizations. These barriers include Information quality, resistance to change, data availability and accessibility, skills deficiency, lack of funds, legal and ethical concerns, and cultural and supply chain incoherencies.

Shrivastav (2021) intended to conduct a systematic and analytical review of the barriers to implementing AI solutions in SCM. The authors first embarked on a systematic literature review to synthesize the available knowledge and insights on the antecedents of AI implementation in supply chains. In this systematic, some factors that may hinder the effectiveness of AI in managing the supply chain are outlined. These barriers include organizational size, workforce resistance to change, lack of understanding of AI, competing priorities, misaligned goals, and high upfront costs associated with AI initiatives.

Similarly, Moktadir et al. (2019) also focus on exploring and analyzing the potential barriers to BDA in the manufacturing supply chain, considering the country of origin, Bangladesh. This study seeks to contribute to this body of knowledge by analyzing these barriers through a Delphi-based analytic hierarchy process (AHP). Questionnaires were administered to five manufacturing firms in Bangladesh. The findings of this research are as follows: (i) Data related barriers are of the most significant importance, (ii) technology-related barriers are the second most important, and (iii) the five most important sub-facets of such barriers are (a) absence of structure (b) data integration issues (c) issues of data privacy (d) non-availability of BDA tools and (e) high costs of investment.

2.4 Gaps in Literature

From the empirical studies, several important gaps in the literature can be identified, providing a basis for this research contribution to knowledge. The literature review identified a meaningful gap related to the lack of theoretical integration for the use of AI-BDA in humanitarian contexts. Related studies have primarily relied on a single theoretical stance to underpin their research; for example, Dubey et al. (2022) employed a practice-based view theory, while other researchers referenced the resource-based view or dynamic capability theory, but did not provide an integration of multiple theoretical perspectives. The current study adopted a more contextual theoretical approach by integrating Socio-Technical Systems Theory, Resource-Based View Theory, and Resilience Theory to provide a more comprehensive theoretical perspective.

A significant gap exists in the literature examining new empirical research on AI-BDA across different developing economies. Previous studies, including systematic reviews and case studies examined in Abhulimen & Ejike (2024), lack sufficient data to demonstrate evidence of AI-BDA in an operational context. The literature does not identify and compare different African contexts, which the current study addresses with its dual-country focus on Ghana and South Africa.

The empirical review reveals a significant gap in the disaggregation of AI-BDA into distinct, measurable techniques. Dubey et al. (2022) considered the effects of AI-BDA on HSCR but did not separate the combined impact of the specific techniques contributing to use cases, such as Time-Series Forecasting, Early Warning Systems, Logistics Optimisation, and Real-Time Monitoring. This study provides empirical evidence of comparative effectiveness found across discrete categories of AI-BDA techniques.

While there is recognition of the challenges for implementation, there is a lack of comprehensive empirical evidence documenting AI-BDA barriers to adoption in HSCs. Theoretical challenges were exposed in studies conducted by Beduschi (2022) and Cai and Zhu (2015), but there has been little systematic focus on identifying and ranking barriers within different organisational contexts.

While existing literature clearly identifies these gaps, collectively they support the need for empirical, theory-based research to close the knowledge gap between AI-BDA's theorised potential and its use in operational contexts related to humanitarian operations.

2.5 Summary of Literature Review

This literature review thoroughly reviews the application of AI-BDA in Humanitarian Supply Chain Operation (HSCO), relying on three theoretical frameworks: Social-Technical Systems Theory, Resource-Based View Theory, and Resilience Theory.

The review establishes that AI and BDA have become innovative technologies in the humanitarian supply chain, fulfilling new and higher capabilities in demand forecasting, logistics and resource deployment. AI comprises various tasks, from predictive analytics and early warning systems to real-time control and optimization functions. At the same time, BDA allows for data processing using advanced analytical methods to support decision-making and optimize organisational performance.

HSCR is a key concept for determining efficient disaster response and relief. The literature underlines that HSCR goes beyond mere robustness to include dynamic capabilities for learning and adaptation in volatile contexts. Other elements of HSCR are pre-assessment capacity, student engagement, strategic planning, timely actions, risk mitigation, and resources.

The literature review reveals that AI-BDA integration positively impacts HSCR, and research has shown that SC performance regarding visibility, efficiency, and resilience has improved. Some notable advantages include improved visibility, effective final mile delivery, tailored solutions, and flexible supply chain solutions as part of the procurement strategy.

Again, the review highlights several challenges and barriers that humanitarian supply chain AI-BDA applicants are bound to encounter. Technological barriers include infrastructure issues, data integration, organizational support and expertise, concerns with cost or money, and human issues such as skill, ability, and receptiveness to change.

Based on the literature review, the proposed AI-BDA integration has the potential to improve the resilience of HSCs; however, its implementation is contingent upon various factors, such as the organization’s readiness, technical readiness, and human factors. The type of review proposed implies a dual perspective on the supply chain and technological evolution that factors both to strengthen this chain. The review suggests a balanced approach considering technological advancement and organizational dynamics in pursuing enhanced supply chain resilience.

CHAPTER THREE

METHODOLOGY

3.0 Introduction

The methodology chapter explains in detail how this research was conducted to examine the use of AI-BDA to increase the resilience of the humanitarian supply chain. This chapter outlines the procedure employed to meet the research objectives of the study and is divided into several specific sections.

The first section of the chapter looks at the research paradigm, focusing on the positivist research philosophy that forms the foundation of this research and why it is suitable for examining AI-BDA applications through data collection and analysis. Subsequently, the research design section presents the explanatory research strategy used to examine the associations between AI-BDA applications and the resilience of HSCs.

The population and sampling section outlines the study's target population as supply chain professionals in Ghana and South Africa and the purposive sampling method, which was used to obtain 200 participants with experience in the field. The data collection procedure section describes primary data collected through an online questionnaire, and the measures section describes the multi-item scales used to measure the theoretical constructs.

The chapter then looks at validity and reliability and how the study ensured that the research instruments used were credible. In the data analysis part, the research method used to achieve each of the research objectives is outlined in detail, namely descriptive statistics, exploratory factor analysis, and structural equation modelling. Last but not least, the ethical considerations section elucidates the precautions taken to ensure that participants' rights and best interests were not violated during the study.

3.1 Research Philosophy

The research paradigm selected for this study is Positivism. The study seeks to assess how AI-BDA could improve resilience in HSCs. By analysing quantitative data and tangible results, the study aims to contribute to the knowledge of the efficiency of AI-BDA techniques in HSCs (Park et al., 2020; Fellow & Liu, 2015).

The positive paradigm is the most appropriate for this study because it allows for the quantitative assessment of the effects of AI-BDA applications on the humanitarian supply chain robustness through data gathering and analysis. Hence, choosing positivism as the philosophy of the study, the researcher agrees that the research must be done systematically and with measurable data. This approach provided insights into how AI-BDA solutions can be applied to solve some of the most important issues in disaster management and the allocation of resources.

Furthermore, since this study aims to measure the efficiency of AI-BDA applications in HSCR, positivism is the most suitable research paradigm for this study. In this regard, the quantitative data and measurable results allowed the study to demonstrate the benefits of using AI-BDA solutions in HSCs and offer recommendations for future applications.

3.2 Research Approach

Research approaches provide fundamental frameworks for structuring investigations and generating knowledge. Researchers intending to provide a theoretical contribution face an uphill task in recognising the considerable range of approaches to theorising, including inductive, abductive, and deductive (Okoli, 2023). These three approaches have different starting points. Inductive theorising begins by examining non-theoretical empirical phenomena, abductive theorising starts with a rudimentary theory or theory-in-progress, and deductive theorising commences with a proposed or supported theory (Okoli, 2023).

Deductive reasoning employs a top-down approach, theorising from general theories to specific conclusions. In a deductive approach, a hypothesis is developed based on existing theory, and a research strategy is designed to test that hypothesis. Positivism aligns itself with the hypothetico-deductive model of science, which focuses on verifying a priori hypotheses predicated on experimentation through the operationalisation of variables and measures (Park et al., 2020). This follows a series of systematic stages, including formulating hypotheses that systematically draw upon a theory, operationalising the hypotheses, testing the hypotheses through relevant methods, and reflecting on the outcomes to confirm or reject the theories.

Inductive reasoning employs a bottom-up approach, starting with specific observations and progressing to broader generalisations. The primary distinction between inductive and deductive reasoning is that inductive reasoning ultimately aims to develop a theory, whereas deductive reasoning seeks to test an existing theory (Streefkerk, 2023). This is very useful when there is limited literature available on a topic; inductive theory development is important because it is inadequate to rely only on theory verification in the pursuit of new knowledge.

Abductive reasoning considers the limitations of both abductive and deductive approaches by seeking the most likely explanation for observed phenomena (Haig, 2005). Abductive reasoning does not involve pre-selecting theories for purposes of verification through hypothesis testing, nor is it interested in establishing theories from secure observations as in inductive reasoning. Abductive reasoning looks to develop hypotheses, inclusive of observations, facts, or phenomena that indicate a new theory may be developed or that previously developed theories may be clarified or refined.

The current study adopted a deductive approach to theorising, consistent with the positivist research paradigm in which this research was situated. First, the deductive approach afforded this research the opportunity to examine causal relationships between concepts and variables, which was essential to examine the effects of AI-BDA techniques on HSCR. Second, the objectives of the study were to test existing theoretical frameworks, including (1) Socio-Technical Systems Theory, (2) Resource-Based View Theory, and (3) Resilience Theory within the context of HSCs. Deductive qualitative analysis provides researchers with the opportunity to be systematic in their approach, employ induction, and refine their theory (Fife & Gossner, 2024).

Third, the deductive approach afforded structured hypothesis testing through quantitative methods, thereby strengthening the research objective of producing generalizable findings. Working hypotheses provide a flexible framework that guides research and fosters coherence across the various stages of a research project (Whetsell & Shields, 2021), making them suitable for the systematic investigation of AI-BDA applications in humanitarian contexts.

3.3 Methodological Choice

This research employed a quantitative research approach from a positivist perspective to investigate the relationship between AI-BDA techniques and HSCR. Positivism is related to the hypothetico-deductive model of science, which builds on the verification of a priori hypotheses and experimentation by operationalising variables and measures and using the results of hypothesis testing to build and contest scientific knowledge (Park et al., 2020). The advantages of quantitative research primarily lie in its ability to generalise, focus on hypothesis testing, and establish causality (Lim, 2025).

A quantitative approach was therefore appropriate for the aims of this study. More specifically, quantitative methods allow for accuracy, objectivity, and the ability to generalise findings to larger populations (Zyoud et al., 2024). The quantitative research approach enabled systematic measurement of the variables and hypothesis testing through structured data collection and statistical analysis. The hypothetico-deductive approach is a circular process in which the researcher's theory, hypothesis, variable generation, operationalisation, experimentation, and refinement of the theory (Slater, 2024) occur.

Furthermore, the quantitative approach was favourable as it enabled an objective exploration of causal relationships between AI-BDA applications and measures of supply chain resilience. As noted by Rogerson (2014), quantitative research is characterised by assumptions aligned with a positivist philosophy that advocates for the objectivity and neutrality of the researcher, as well as the verification and testing of existing theories (Maksimovic & Evtimov, 2023). As such, the research approach enabled the generation of empirically based findings that are suitable for generalisation to broader humanitarian contexts and may support evidence-based managerial decisions regarding the management of HSCs.

3.4 Research Design

This study employs an exploratory research design to investigate the integration of AI-BDA techniques in HSCs and their impacts on supply chain resilience. The exploratory design is particularly justified for this study, given the nascent and emerging nature of AI-BDA applications in humanitarian contexts, which have minimal empirical research and a fragmented literature (Saunders et al., 2019; Neuman, 2014).

Exploratory research is most applicable for investigating emerging, newly researched, or under-researched phenomena where limited prior knowledge and understanding exist (Babbie, 2017; Creswell & Creswell, 2018). The reason AI-BDA integration in HSCs represents a newly emerging field with scattered theoretical frameworks and limited implementation studies of practical use is that an exploratory approach provides a systematic investigation into and understanding of these new applications without being constrained by prior assumptions of the theories or frameworks used (Robson & McCartan, 2016).

The exploratory design enables researchers to investigate the current adoption of AI-BDA techniques in HSCs, their impacts on resilience, and the barriers to implementation. All of these areas have been relatively unexplored in current research (Kumar, 2019). The exploratory research design also has distinct value when the research objectives are to discover patterns, identify key variables, and/or develop an understanding of the complexities of a phenomenon (Malhotra et al., 2017).

Lastly, the exploratory design of the study influences the study aims, which incorporate a qualitative approach to advance substantive insights about the nature of this emerging field and guide future research and practice. Exploratory research differs in focus and depth of investigation from explanatory research, which is concerned with testing different established relationships between defined variables. Whereas explanatory research seeks to develop insights and a deeper understanding of a phenomenon, enabling further exploration (Sekaran & Bougie, 2016; Zikmund et al., 2018).

3.3 Population of the Study

The population for this study is 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 (Boafo et al., 2020). The country's evolving digital infrastructure and increasing AI-BDA adoption make it a relevant context for examining the role of emerging technologies in disaster management (Abid et al., 2021). 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 (Samuels, 2017). 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 operation-al 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.

3.4 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 HSCs. 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 (Ames et al., 2019). Convenience sampling was also incorporated due to the challenge of accurately determining the total population of AI-BDA practitioners in HSCs. 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 HSCR (Dubey et al., 2018; Dennehy et al., 2021). 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 (Adrian et al., 2018).

While purposive and convenience sampling offer advantages in accessing knowledgeable participants, they also introduce potential selection bias and limited generalizability. Purposive sampling may lead to overrepresentation of professionals with specific viewpoints, while 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 specialization, the study enhanced the credibility and applicability of its findings within the humanitarian supply chain domain.

3.5 Data Collection Procedure

3.6 Source of data

This study adopted primary data as the source of data. The data collected in this study to achieve its objectives were mainly collected through an online survey through Google Forms, which is noted for its accessibility and user-friendly interface (Sofi-Karim et al., 2023).

To minimize incomplete responses, the online survey was designed with built-in validation features that prevented submission of incomplete questionnaires. The Google Forms platform was configured with mandatory response requirements for all questions, ensuring that participants could not proceed without completing each section. This technical approach eliminated the possibility of partially completed surveys being submitted.

First, the research questions and relevant literature informed the creation of structured online questionnaires to collect the data used in the study. The survey instrument was developed to solicit information on AI-BDA techniques, their effectiveness, and the challenges and barriers in HSCs. The questionnaire used structured close-ended questions and Likert scales to collect information on the use of AI-BDA in humanitarian supply chain environments. The questionnaire was pre-tested with 30 experts in the field before the full deployment to check for the questions' comprehension, appropriateness, and accuracy (Jain et al., 2016). The pilot study results were used to make changes to the final questionnaire.

The review questionnaire was sent to professionals from different humanitarian organisations in Ghana and South Africa, such as supply chain managers, data analysts, IT personnel and operations managers. The initial communication happened through professional contacts and mailing lists from humanitarian organisations. This was followed up with formal invitation emails, which included the survey along with a description of the research. Each participant received a tailored invitation detailing how the research related to their work, how participation could help them improve, and explaining the relevance of their responses to the research. The invitations also focused on how the research findings would range from alternatives to improve humanitarian supply chain operations, and this kind of investment in outcomes would incite a commitment, as opposed to a knowledge contribution.

The study pursued a follow-up approach that was persistent but respectful. In a series of reminder emails spaced a week apart (one week, two weeks, and three weeks), we offered a personal touch by including our response progress, which gave participants a sense of a community taking part in something. After the second reminder, if there was no response, the researcher phoned to check to see if they had any concerns or technical issues.

All the participants' information remained anonymous, and the subjects agreed to complete the survey (Petrova et al., 2016). The data collected was downloaded and stored in a secured password-protected computer, which was only accessible to the researcher. Data collection was done in a manner that complied with ethical research standards and data protection regulations.

3.7 Conceptual Framework

The conceptual model shown in Figure 2.1 proposes a holistic process of implementing AI-BDA applications in HSC to enhance their resilience. The first framework stage is the input level, which signifies the adoption of AI-BDA applications in HSCs. These technologies have the potential to transform significantly the ways through which humanitarian organizations foresee and allocate their supply chain requirements.

However, the framework suggests that this integration is not straightforward. It incorporates a crucial moderating element: challenges and barriers that influence AI-BDA implementation in HSCs. At the framework's core, AI-BDA is integrated into HSC operations. This step includes deploying and customizing AI-BDA technologies to address the opportunities and challenges in the humanitarian supply chain. The framework then points to two key outcomes from this integration process as the final step of creating an integrated mediator. The first and arguably the most significant improvement is increasing the general resilience of HSCs. The second output relates to the generation of best practices and recommendations.

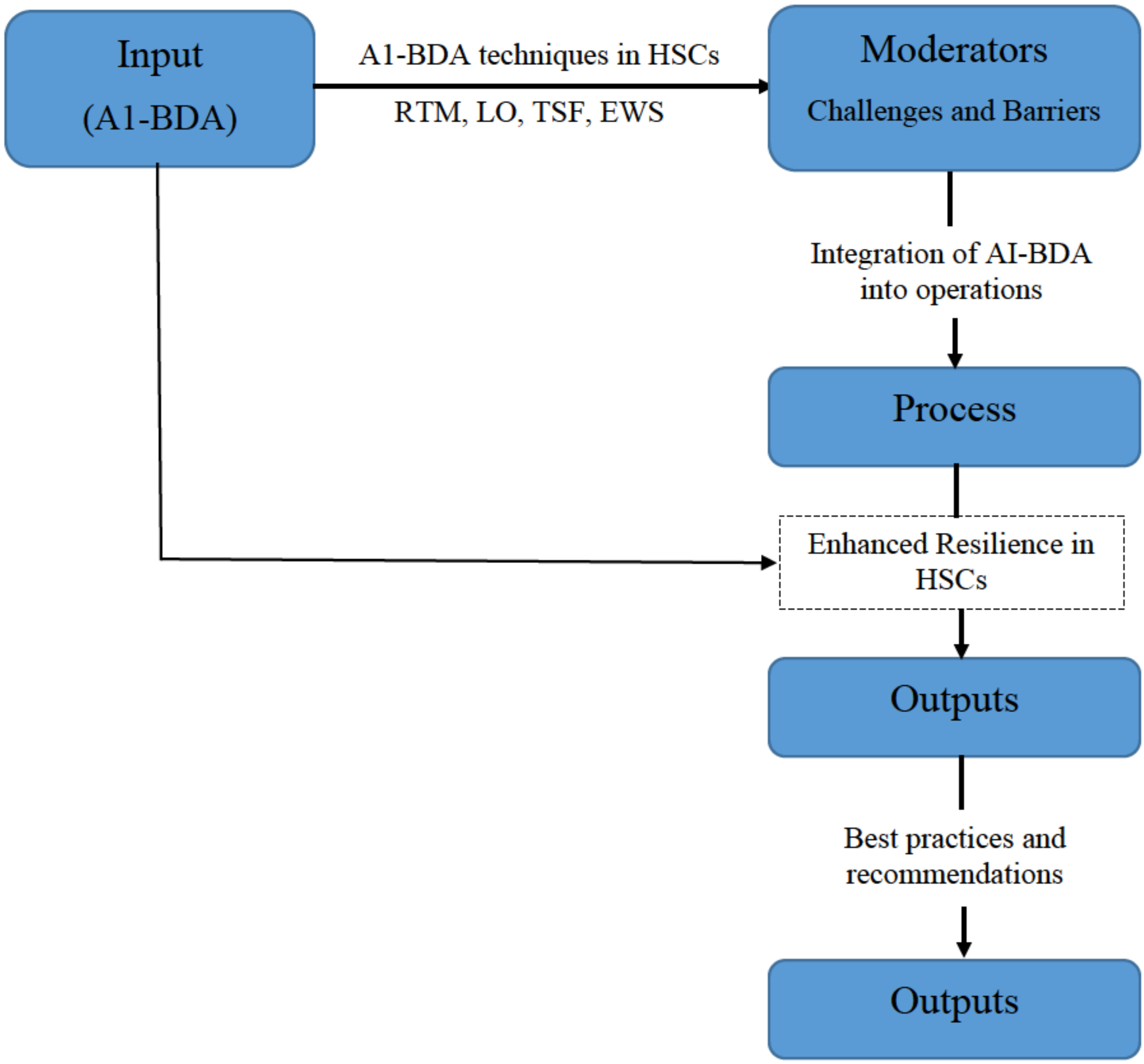

Figure 3.2 Conceptual Framework (Author's Construct)

3.8 Measures

The researcher utilised multi-item scales to measure the constructs of the theoretical model, as presented in Fig. 3.1. The specific items that were used to measure the constructs are presented in Table 3.1 below. The items used to measure the constructs were adapted from previous studies, as indicated in the Table 3.1 below.

Table 3.1 Measurement scales

Construct	Item	Statement	Source
AI-BDA techniques in HSCs	TSF1	Our organisation uses AI for demand prediction in humanitarian operations	(Adapted from (Sahebi & Jafarnejad, 2018; Chan et al., 2015; Shah et al., 2023)
	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 Hasan et al., 2023; Tomas et al., 2022)
	EWS2	We use AI-powered systems for flood susceptibility prediction.	
	EWS3	Our early warning systems help pre-position supplies before disasters.	
	LO1	Our organisation uses AI algorithms to optimise delivery routes during crises.	(Adapted from Ortuño et al., 2021; Serrato-Garcia et al., 2016; Abhulimen & Ejike, 2024)
	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. 2016; Yang et al., 2011; Budak et al., 2020)
	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-driven technologies.	Adapted from Altay et al. (2018); Papadopoulos et al. (2017)
	HSCR2	Information gathered using AI-driven technology help us provide necessary relief materials during unexpected disruptions.	
	HSCR3	We maintain a buffer stock of important relief items to tackle demand and supply uncertainties.	
	HSCR4	We quickly repair the damages caused to the basic property, schools, and other essential centres.	
Challenges and barriers	TB1	Our organisation faces infrastructure limitations in implementing AI-BDA	(Adapted from Moktadir et al., 2019; Bag et al., 2022)
	TB2	Data integration complexity poses a significant challenge.	
	TB3	Limited data accessibility hinders our AI-BDA implementation.	
	OB1	Lack of top management support affects our AI-BDA implementation	(Adapted from Raut et al., 2021; Bag et al., 2022)
	OB2	Our organisation faces resistance to change in adopting AI-BDA.	
	OB3	Cultural barriers affect our AI-BDA implementation.	
	RB1	Financial constraints limit our AI-BDA implementation	(Adapted from (Kabra et al., 2023; Bag et al., 2022; Dehkhodaei et al., 2023)
	RB2	Skill gaps among staff affect our adoption of AI-BDA.	
	RB3	Lack of technical expertise hinders our AI-BDA implementation.	

Technology Readiness (TR)	TR1	AI-BDA improve our ability to respond quickly to supply chain disruptions.	Adapted and modified from Parasuraman and Colby (2015).
	TR2	The use of advanced technologies helps our organization deliver aid more efficiently.	
	TR3	Our organization 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 organization 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.	

3.9 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. The questionnaire's content validity was checked by experts in humanitarian supply chain management and AI (Fielsam-Adams et al., 2015). 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 (Mehmetoglu, 2015; Kundu et al., 2023). Discriminant validity were tested by comparing the square root of AVE with correlations between the construct and other constructs in the research model and ensuring that each construct was different from all other constructs (Firman et al., 2021; Janadari et al., 2016). However, Fornell and Larcker (1981) criterion fails to detect 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. (2015), the HTMT test is a more robust method to assess discriminant validity in variance-based structural equation modelling, outperforming the Fornell-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 (Hart, 2019). The face validity of the questionnaire was checked by modifying it several times according to the suggestion of the academic supervisor in the field (Bastani et al., 2015). The final instrument was also piloted for comprehension and simplicity to ensure that the target respondents could effectively comprehend and properly answer the questions posed (Lenzner, 2014). 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.

The following was done to ascertain the reliability of the research instrument. Cronbach's alpha coefficient was used to determine the data's internal consistency reliability, and a coefficient above 0.7 was considered satisfactory for research (Kılıç, 2016; Samuels, 2017). In addition, a pilot survey was administered with 30 participants from the population of interest from humanitarian organisations to assess the instrument's validity and to determine any issues related to the questions in the questionnaire (Chen & Wilson, 2023).

3.10 Data Analysis

The data analysis process was completed through a systematic, multi-phase approach aimed at thoroughly exploring the research question area, with specific statistical considerations and ensuring legitimacy. All data analyses were conducted utilising SPSS version 27.0, and extra data preparation was done using Microsoft Excel.

The data analysis began with a thorough data preparation and screening process to ensure the data's quality and usability for subsequent statistical analyses. All raw survey data downloaded from Google Forms were converted to SPSS format and analysed for completeness, accuracy, and consistency.

The first step involved a systematic review of all 200 submissions to ensure completeness and accuracy. Each variable was examined for out-of-range values and logical errors. All string variables were standardised to control the data formatting, and all categorical variables were recoded into a numerical representation that could be used in the statistical analyses. The Google Forms survey platform required mandatory respondent answers, which virtually eliminated missing values. This meant that all participants had fully completed all meaningful datasets.

Prior to conducting the planned primary statistical analyses of the data, thorough assumption tests were performed to ensure that the selected analyses were most feasible, and alternative suggestions could be made if necessary. The first analyses conducted were normality and multicollinearity tests, which are often necessary to complete further statistical analyses (AlAnazi et al., 2016).

$$Normality, f(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{\frac{-(x-\mu)^2}{2n^2}} \text{.................... (Eqn 1)}$$

Where,

μ is the mean,

σ is the standard deviation,

x is the variable of interest.

$$\text{Multicollinearity}, VIF_j = \frac{1}{1-R_j^2} \text{............... (Eqn 2)}$$

Where,

R_j^2 is the coefficient of determination of the regression of the *j-th* predictor on all other predictors.

To meet the first research question that focused on examining the existing AI-BDA techniques in HSCs, the means and standard deviations were determined to analyse the patterns of applying the techniques. These analyses gave an understanding of the most frequent techniques applied and their significance in boosting supply chain resilience (Cisterna et al., 2021).

$$Mean, x = \frac{1}{n}\sum_{i=1}^{n} x_i \text{...................... (Eqn 3)}$$

Where,

n is the number of observations,

x_i are the data values.

$$\text{Standard deviation}, \sigma = \sqrt{\frac{\sum_{i=1}^{n}(x_i - x)^2}{n}} \text{ .... (Eqn 4)}$$

Where,

n is the number of observations,

x_i are the data values.

x is the mean

More importantly, 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 (Conway & Huffcutt, 2003).

$$X = \Lambda F + \epsilon \text{ .... (Eqn 5)}$$

X is the observed data matrix,

Λ is the loading matrix (factor loadings),

F is the factor matrix (latent variables),

ϵ is the error matrix.

To achieve the second objective, which focused on determining the effectiveness with which AI-BDA applications boost the resilience of the humanitarian supply chain, inferential statistics were used to test hypotheses on the relationship between AI-BDA integration and the resilience of the humanitarian supply chain. This study adopted regression analysis, a potent analytical method for assessing the relationship between variables, to assess the effectiveness of AI and BDA techniques on HSCR dimensions. Conversely, the regression analysis was utilised to test hypotheses that have been formulated (whether alternative or null hypotheses).

Regarding the third objective aimed at determining the barriers to the implementation of AI-BDA, exploratory factor analysis was conducted with only those factors contributing to the AI-BDA adoption constraints, which were considered based on eigenvalue greater than one and factor loading greater than 0.5 (Conway & Huffcutt, 2003). This approach was used to simplify the dataset and extract its basic components that could be generalised to general themes like technical, organisational and resource-related barriers. Research has shown that factor analysis in data synthesis is effective when examining adoption barriers in emerging technology contexts (Field, 2018). Moreover, a descriptive statistic was conducted calculating the means and standard deviations. A mean value ranking analysis was used to rank the most prominent barrier to the least prominent barrier.

3.11 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 organization's capacity to adopt and utilize emerging technologies such as AI and BDA. Organizations 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 organization’s preparedness to adopt it (Parasuraman & Colby, 2015). TR acts as an enabler and moderating factor that shapes both the likelihood and effectiveness of AI-BDA integration. Organization Size (OS), typically measured by the number of employees, is another critical confounder. Larger organizations often have more resources—financial, technological, and human capital—that make AI-BDA implementation more feasible and effective (Woolley et al., 2023). 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 (Wooldridge, 2013). Hence the model specification for this study is:

$$HSCR = a + \beta 1TSF + \beta 2EWS + \beta 3LO + \beta 4RTM + \beta 5OS + \beta 6TR + \varepsilon \qquad \text{(Eqn 6)}$$

$$HSCR = a+\beta 1AIBDA + \varepsilon \qquad \text{(Eqn 7)}$$

Where;

HSCR – Humanitarian Supply Chain Resilience

AI-BDA – Artificial Intelligence and Big data analytics techniques

TSF – Time-Series Forecasting

EWS – Early Warning Systems (EWS)

LO – Logistics Optimization (LO)

RTM – Real-time Monitoring

OS – Organisation Size (measured by the number of employees in the organisa-tion)

TR – Technology Readiness (measured using the adapted Technology Readiness In

dex (TRI 2.0) framework)

a – Intercept

β1: β4 – Coefficients

ε – error term

3.12 Ethical Considerations

Due to the sensitivity of the study respondents, their privacy and safety were assured through ethical considerations throughout the research. First, respondents were assured and provided written informed consent, and the purpose of the study was explained, along with its adverse effects and benefits. They were assured of their right to withdraw from the study without any consequences. To ensure the participants' confidentiality and the anonymity of their responses, all data were safeguarded and only available to authorised personnel.

Contingency measures were put in place to ensure that the respondents were not harmed or discomforted. Such measures included ensuring that participants who may experience some level of discomfort during the study receive support. In addition, all respondents' rights and respect for their dignity were observed and protected during the entire research process. Cultural and diversity issues were also considered in the data collection and data analysis process.

The research followed the ethical procedures of Durban University of Technology and the rules and regulations for conducting research in the country and internationally. This was done by ensuring that the study received approval from the university's ethical committee before data collection, ensuring that the research design and procedures used in the study were ethical, and responding to any ethical issues that may have arisen during the course of the study. Furthermore, the researcher ensured that all the respondents were well accompanied and sensitised on how their data would be used and protected.

CHAPTER FOUR

RESULTS AND DISCUSSIONS

4.0 Introduction

This chapter reports the findings of the research study on how AI-BDA can be adopted and used in HSCs. It covers the demographic and organisational profiles, AI-BDA adoption, supply chain resilience effectiveness, and barriers to its implementation. The chapter starts with demographics and shows how different the respondents were regarding age, gender, education, professional roles, and experience. Organisational profiles are also analysed, including their geographical distribution, types of organisations, and operational focus.

This chapter investigates three broad goals through rigorous statistical methods. First, it assesses the current AI-BDA methods in HSCs for four significant components: Time-Series Forecasting, Early Warning Systems, Logistics Optimization, and Real-time Monitoring. Second, it quantifies whether AI-BDA programs contribute to HSCR using regression. Finally, it explores the barriers to AI-BDA adoption based on technical, organisational and resource challenges.

The analysis employs statistical approaches, such as reliability analysis, measurement validation, exploratory factor analysis and descriptive statistics to ensure robust findings. The chapter's content moves from measurement validity using Cronbach's Alpha coefficients and factor loadings to an in-depth discussion of each research objective for an exhaustive look at the application of AI-BDA in humanitarian supply chain operations.

4.1 Response Rate

A total of 200 respondents was the target sample size for the study. The number of responses that were received from the respondents was 200, representing 100.0%. The Google Forms platform's mandatory response requirements eliminated incomplete submissions, ensuring a complete dataset for analysis.

4.2 Demographic Information

Table 4.1 shows the demographic information of the respondents in humanitarian organisations.

Table 4.2 Demographic Information

Variable		Frequency	Percent
Age	Under 25	41	20.5
	25-34	37	18.5
	35-44	30	15.0
	45-54	49	24.5
	55 and above	43	21.5
Gender	Female	111	55.5
	Male	89	44.5
Education	Secondary School	33	16.5
	Bachelor's Degree	34	17.0
	Master's Degree	31	15.5
	Doctorate	24	12.0
	Professional Certification	39	19.5
	Other	39	19.5
Professional Role	Data Scientist	35	17.5
	IT Specialist	39	19.5
	Operations Leader	57	28.5
	Supply Chain Manager	33	16.5

	Other	36	18.0
Experience in Humanitarian Supply Chain	Less than 3 years	60	30.0
	3-5 years	45	22.5
	6-10 years	44	22.0
	More than 10 years	51	25.5

Respondents' ages represent a fair proportion of life years, with most respondents in the middle-to-upper age bracket. Professionals between the ages of 45-54 make up 24.5% of the total respondents, and those over 55 make up 21.5%. There are also younger demographics under 25 years, representing 20.5% of the population; 25-34 and 35-44 represent 18.5% and 15.0%, respectively. This age diversity provides depth to the research by drawing on conventional knowledge and contemporary technological insights.

Gender composition reveals a slightly higher number of female respondents (55.5% vs 44.5% males). This relatively equal gender distribution suggests changes in workplace culture in the humanitarian sector and indicates that the results reflect differential perspectives about decisions and operational activities.

The educational background of respondents indicates a highly skilled labour force. Those with professional certifications and other qualifications are represented by 19.5% and 17.0% of respondents, respectively. Secondary school graduates represent 16.5%, Master's degree holders, 15.5% and Doctorate holders, 12.0%. This educational profile shows a good theoretical background among respondents, indicating the ability to conceptualise and implement advanced technology solutions in HSCs.

In the industry, professional roles are particularly diverse, with Operations Leaders accounting for the highest proportion at 28.5%. IT Professionals comprise 19.5% of respondents, and Data

Scientists comprise 17.5%. Supply Chain Managers represent 16.5% of the total; other positions make up 18.0%. Such interdisciplinary backgrounds ensure a detailed understanding of the technical and managerial aspects of AI-BDA implementation.

Experience levels within the humanitarian supply chain illustrate a particular trend. Most professionals have less than 3 years' experience (30.0%), followed by those with 10+ years' experience (25.5%). 3-5 years and 6-10 years of experience account for 22.5% and 22.0% respectively. This distribution reflects a sector where talent is retained, and new recruits are introduced.

4.3 Organisational Information

Table 4.2 below shows the organisational information of the respondents.

Table 4.3 Organisation Information

Variable		Frequency	Percent
Country of Operation	Ghana	69	34.5
	South Africa	70	35.0
	Both countries	61	30.5
Type of Humanitarian Organization	Government Agency	31	15.5
	International NGO	45	22.5
	Local NGO	43	21.5
	United Nations Agency	39	19.5
	Other	42	21.0
Primary Area of Supply Chain Operations	Disaster Response	35	17.5
	Food Distribution	36	18.0
	Logistics and Transportation	42	21.0
	Medical Supply Chain	22	11.0

	Warehouse Management	34	17.0
	Other	31	15.5
Years of Organization's Experience with AI-BDA	Less than 1 year	51	25.5
	1-3 years	52	26.0
	4-5 years	42	21.0

The geographical distribution of operations shows a relatively balanced representation across the target regions. South Africa accounts for slightly higher representation at 35.0% of operations, closely followed by Ghana at 34.5%. A significant proportion of organisations (30.5%) operate in both countries, indicating substantial cross-border humanitarian operations. This distribution suggests a good comparative basis for understanding how AI-BDA implementation may vary across African contexts and regulatory environments.

The diversity in types of humanitarian organisations provides a comprehensive view of the sector. International NGOs represent the largest segment at 22.5%, followed closely by Local NGOs at 21.5%. United Nations Agencies comprise 19.5% of respondents, while Government Agencies account for 15.5%. The remaining 21.0% represent other organisational types. This distribution reflects the complex ecosystem of humanitarian operations, combining international expertise with local knowledge and governmental authority.

Regarding primary supply chain operations, the study reveals diverse operational focuses. Logistics and Transportation emerge as the dominant area, representing 21.0% of operations. Food Distribution follows at 18.0%, while Disaster Response accounts for 17.5% of operations. Warehouse Management comprises 17.0%, and Medical Supply Chain operations represent 11.0% of the sample. The remaining 15.5% engage in other operational areas. This operational diversity suggests varying levels of complexity and urgency in humanitarian supply chain management, each potentially benefiting differently from AI-BDA implementation.

The organisations' experience with AI-BDA reveals an emerging technological landscape. Many organisations are in the early stages of AI-BDA adoption, with 25.5% having less than one year of experience and 26.0% having 1-3 years of experience. Organisations with 4-5 years of experience comprise 21.0% of the sample. This distribution suggests that AI-BDA implementation in HSCs is still in its early phases, with organisations at various stages of the adoption curve.

4.4 Measurement Scales

Table 4.4 Reliability Analysis

Construct	No. of items	Cronbach Alpha
AI-BDA techniques	12	0.83
Humanitarian supply chain resilience (HSCR)	4	0.79
Time-Series Forecasting (TSF)	3	0.81
Early Warning Systems (EWS)	3	0.82
Logistics Optimization (LO)	3	0.80
Real-Time Monitoring (RTM)	3	0.78
Technology Readiness (TR)	10	0.84
Barriers to adopting and implementing AI-BDA	9	0.91

The reliability analysis results presented in Table 4.3 indicate strong internal consistency across all constructs examined in this study. The AI-BDA techniques construct, consisting of 12 items, achieves a Cronbach's Alpha of 0.83, exceeding the widely accepted threshold of 0.70, which signifies good reliability. Similarly, the HSCR construct, measured using 4 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 (EWS), Logistics Optimization (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 an Alpha coefficient of 0.84, indicating excellent reliability. The construct measuring barriers in adopting and implementing AI-BDA shows excellent reliability with a Cronbach's Alpha of 0.91 across nine items.

4.5 Measurement validation

4.5.1 Convergent validity

From Table 4.4, 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 Optimization (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 (EWS) 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 relia-bility in capturing predictive analytics capabilities. Real-Time Monitoring (RTM) items also exhibit substantial loadings between 0.72 and 0.88. The Average Variance Extract-ed (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.

For the 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 sup-ply 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.

Table 4.5 Convergent validity

Construct	Item	Factor Loadings	Average Variance Extracted (AVE)
AI-BDA techniques (α=0.83)	TSF1	0.83	0.74
	TSF2	0.88	
	TSF3	0.88	
	EWS1	0.92	
	EWS2	0.85	
	EWS3	0.76	
	LO1	0.92	
	LO2	0.96	
	LO3	0.82	
	RTM1	0.72	
	RTM2	0.88	
	RTM3	0.86	
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 (EWS) (α=0.82)	EWS1	0.86	0.72
	EWS2	0.89	
	EWS3	0.80	
Logistics Optimization (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	
	TB1	0.85	0.73

Barriers to AI-BDA adoption and implementation (α=0.91)	TB2	0.88
	TB3	0.83
	OB1	0.86
	OB2	0.89
	OB3	0.82
	RB1	0.87
	RB2	0.84
	RB3	0.86

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 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.

The barriers construct shows consistently high factor loadings in all nine elements (from 0.82 to 0.89). Items of Technical Barriers (TB) have loadings between 0.83 and 0.88, Organizational Barriers (OB) have loadings between 0.82 and 0.89, and Resource Barriers (RB) have loadings between 0.84 and 0.87. OB2 has the maximum loading (0.89), and OB3 has the minimum loading (0.82). This AVE of 0.73 means the construct accounts for 73% of the variance in its measured items, well beyond the 0.5 limit.

4.5.2 Discriminant Validity

From Table 4.5 below, the discriminant validity analysis confirms strong construct distinction within the measurement model. Following the Fornell and Larcker (1981) 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—AI-BDA Techniques, HSCR, TSF, EWS, LO, RTM, TR and barriers—satisfy this criterion, demonstrating that each construct measures a unique theoretical concept.

Table 4.6 Discriminant validity

Constructs	AI-BDA Techniques	HSCR	TSF	EWS	LO	RTM	TR	Barriers
AI-BDA Techniques	**0.859**							
HSCR	0.523	**0.865**						
TSF	0.498	0.487	**0.846**					
EWS	0.512	0.475	0.525	**0.853**				
LO	0.538	0.498	0.522	0.544	**0.849**			
RTM	0.476	0.460	0.507	0.531	0.510	**0.835**		
TR	0.529	0.482	0.493	0.520	0.533	0.488	**0.854**	
Barriers	0.543	0.456	0.467	0.650	0.560	0.510	0.456	**0.856**

Table 4.7 HTMT Ratios (Discriminant Validity Assessment)

Constructs	AI-BDA Techniques	HSCR	TSF	EWS	LO	RTM	TR	Barriers
AI-BDA Techniques	**1.000**							
HSCR	0.70	**1.000**						

TSF	0.78	0.65	**1.000**					
EWS	0.73	0.61	0.74	**1.000**				
LO	0.76	0.63	0.71	0.70	**1.000**			
RTM	0.68	0.59	0.69	0.66	0.71	**1.000**		
TR	0.74	0.67	0.72	0.70	0.73	0.69	**1.000**	
Barriers	0.70	0.62	0.73	0.68	0.70	0.74	0.72	**1.000**

Source: SPSS (2024)

HTMT values below 0.85 (or 0.90 in some lenient cases) suggest good discriminant validity (Henseler et al., 2015). All values in Table 4.6 above are below 0.85, indicating that the constructs demonstrate adequate discriminant validity.

4.6 Objective 1: AI-BDA techniques in HSCs

4.6.1 Exploratory factor analysis (EFA)

An EFA was performed using a principal component analysis and varimax rotation. The minimum factor loading criteria was set to 0.50 informed by Conway & Huffcutt (2003) 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.

An important 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 indicates 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.

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 gathers items EWS1 to EWS2, which represents Early Warning Systems (EWS). Component 3 includes items LO1 to LO3, referring to Logistics Optimization (LO). Finally, component 4 includes items RM1 to RM3, referring to Real-time Monitoring (RTM). Factor Loadings are presented in Table 4.7 below.

Table 4.8 Component Matrix

Rotated Component Matrix[a]				
	Component			
	1	2	3	4
TSF1	**.528**			
TSF2	**.754**			
TSF3	**.661**			
EWS1		**.660**		
EWS2		**.876**		
EWS3		**.925**		
LO1			**.770**	
LO2			**.575**	
LO3			**.886**	
RM1				**.990**
RM2				**.538**
RM3				**.705**

Extraction Method: Principal Component Analysis

Rotation Method: Varimax with Kaiser Normalization.

a. Rotation converged in 6 iterations.

4.6.2 Descriptive statistics

Table 4.9 AI-BDA techniques in HSCs

	Items	Mean	SD
TS1	Our organisation uses AI for demand prediction in humanitarian operations	3.97	1.412
TS2	We employ machine-learning algorithms for supply chain disruption forecasting.	2.98	1.432
TS3	Our organisation utilises predictive analytics for medical inventory management.	2.99	1.412
EWS1	Our organisation employs machine learning for disaster risk prediction	2.94	1.434
EWS2	We use AI-powered systems for flood susceptibility prediction.	2.81	1.455
EWS3	Our early warning systems help pre-position supplies before disasters.	4.13	1.355
LO1	Our organisation uses AI algorithms to optimise delivery routes during crises.	2.97	1.447
LO2	We employ multi-objective optimisation models for resource allocation.	4.02	1.376

LO3	Our organisation uses AI for transportation network optimisation.	2.97	1.476
RM1	Our organisation employs real-time tracking systems for supply visibility	3.03	1.339
RM2	We use AI to monitor resource distribution in real time.	2.90	1.500
RM3	Our organisation utilises technology for real-time location tracking of humanitarian supplies.	3.09	1.435

Table 4.8 reveals that adopting the AI-BDA technique varies across different areas. The highest mean scores are observed in EWS3 (4.13) and LO2 (4.02), 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 3.97. These scores, above the midpoint of 3.0, indicate above-average implementation levels.

Conversely, several techniques show lower adoption levels, with EWS2 having the lowest mean (2.81), followed by RM2 (2.90) and EWS1 (2.94). 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.

4.7 Objectives 2: Effect of AI and Big Data (AI-BDA) techniques on HSCR

4.7.1 Diagnostic Test

Before the regression analysis was performed a diagnostic test involving a multi-collinearity and normality test were performed. Multicollinearity was assessed using variance inflation factors (VIF). The VIF values for the predictors ranged from 1.2 to 4.8 as shown in Table 4.12 suggesting that multicollinearity is not a major concern in this model.

Normality test was assessed using Shapiro-Wilk test. All variables as shown in Table 4.9 demonstrate normal distribution patterns according to 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 4.10 Normality Test

	Kolmogorov-Smirnov[a]			**Shapiro-Wilk**		
	Statistic	df	Sig.	Statistic	df	Sig.
Time-Series Forecasting (TSF)	.081	200	.200*	.977	200	.325
Early Warning Systems (EWS)	.069	200	.200*	.983	200	.419
Logistics Optimization (LO)	.073	200	.200*	.985	200	.468
Real-Time Monitoring (RTM)	.065	200	.200*	.988	200	.527
HSCR	.078	200	.200*	.981	200	.378
Technology Readiness (TR)	.064	200	.200*	.984	200	.446
Organization Size (OS)	.089	200	.132	.979	200	.354

4.7.2 Hypothesis Testing

This this section used regression analysis to test the hypotheses and compare the relationship between AI-BDA techniques and HSCR. Table 4.10 shows the regression model summary findings, with the coefficient of determination indicating how much the predictor variable influences the dependent variable. Table 4.11 shows the analysis of variance, which shows how well the model describes the relationship, and Table 4.12 shows the regression coefficients, which shows the magnitude of the effect of independent variables on the dependent variable.

Table 4.11 Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.918[a]	.844	.812	.22561

a. Predictors: (Constant), AI-BDA, TS1, EWS, LO, RTM, OS, TR

The R-value of 0.918 suggests that AI-BDA techniques, TSF, EWS, LO, RTM, OS, and TR collectively have a strong influence on HSCR. The R-Square is 0.844, as seen in Table 9. This means that 84.4% of the variance in HSCR is explained by the model's predictor variables. Other factors not included in the model account for the remaining 15.6 percent 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.

Table 4.12 ANOVA

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	28.324	7	4.046	148.40	.000[b]
	Residual	5.235	192	0.027		
	Total	33.56	199			

a. Dependent Variable: HSCR

b. Predictors: (Constant), AI-BDA, TS1, EWS, LO, RTM, OS, TR

The ANOVA test of the model's capability is shown in Table 4.11, 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, meaning the predictors collectively have a significant impact on HSCR.

Table 4.13 Coefficients[a]

Model		Unstandardised Coefficients		Standardised Coefficients	t	Sig.	VIF
		B	Std. Error	Beta			
1	(Constant)	.873	1.698		.514	.298	
	AI-BDA	0.279	0.012	22.560	22.560	0.00	1.025
	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

The results in Table 4.12 indicate that AI-BDA techniques (B = 0.279, p < 0.001) have a positive and significant effect on HSCR, highlighting the critical role of AI-BDA techniques in improving the resilience of HSCs. Hence, the alternate hypothesis (HA1) is accepted, and the null hypothesis (HA0) is rejected. 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 (HB1, HC1, HD1, HE1) are accepted.

Examining the relative effects of the AIBDA techniques, the results reveals Time-Series Forecasting (TSF) (B = 0.231, p < 0.001), Logistics Optimization (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, optimized logistics, and real-time tracking significantly contribute to enhancing the adaptability and efficiency of humanitarian operations.

Similarly, Early Warning Systems (EWS) ($B = 0.186$, $p < 0.001$) 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.

4.8 Objective 3: Barriers to adopting and implementing AI-BDA within HSCs

4.8.1 Exploratory factor analysis (EFA)

An EFA was performed using a principal component analysis and varimax rotation. The minimum factor loading criteria was set to 0.50 informed by Conway & Huffcutt (2003) 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.

An important 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 ($n = 200$) = 40.683 ($p < 0.001$), which indicates its suitability for factor analysis. The Kaiser–Meyer–Olkin measure of sampling adequacy (MSA), which indicates the appropriateness of the data for factor analysis, was 0.713. In this regard, data with MSA values above 0.500 are considered appropriate for factor analysis. Finally, the factor solution derived from this analysis yielded three scale components, accounting for 61.842 per cent of the variation in the data.

The three components identified as part of this EFA aligned with the theoretical proposition in this research. Component 1 includes items TB1 to TB3, referring to Technical Barriers (TB). Component 2 gathers items OB1 to OB2, which represents organisational barriers. Finally, Component 3 includes items RB1 to RB3, referring to Logistics Optimization (LO). Finally, Factor 4 includes items RM1 to RM3, referring to Resource barriers. Factor Loadings are presented in Table 4.13.

Table 4.14 Component Matrix

Rotated Component Matrix[a]			
	Component		
	1	2	3
TB1	**.855**		
TB2	**.816**		
TB3	**.684**		
OB1		**.659**	
OB2		**.548**	
OB3		**.829**	
RB1			**.703**
RB2			**.518**
RB3			**.637**

Extraction Method: Principal Component analysis
Rotation Method: Varimax with Kaiser Normalization.
a. Rotation converged in 7 iterations

4.8.2 Descriptive statistics

Table 4.15 Barriers to adopting and implementing AI-BDA within HSCs

	Items	Mean	SD	Rank
TB1	Our organisation faces infrastructure limitations in implementing AI-BDA	2.94	1.438	6th
TB2	Data integration complexity poses a significant challenge.	3.08	1.390	3rd

TB3	Limited data accessibility hinders our AI-BDA implementation.	3.03	1.459	4th
OB1	Lack of top management support affects our AI-BDA implementation	2.91	1.472	7th
OB2	Our organisation faces resistance to change in adopting AI-BDA.	2.90	1.430	8th
OB3	Cultural barriers affect our AI-BDA implementation.	2.89	1.369	9th
RB1	Financial constraints limit our AI-BDA implementation	3.00	1.398	5th
RB2	Skill gaps among staff affect our adoption of AI-BDA.	3.22	1.477	1st
RB3	Lack of technical expertise hinders our AI-BDA implementation.	3.09	1.476	2nd

Table 4.14 summarises the barriers humanitarian organisations face when deploying AI-BDA in HSCs by mean scores. The highest ranked barrier is **skill gaps among staff (RB2),** with the highest mean score of 3.22 (SD = 1.477), thus making workforce training and development in AI-BDA a considerable priority. This is followed by a **lack of technical expertise (RB3)** (Mean = 3.09, SD = 1.476) in the second rank and **data integration complexity (TB2)** (Mean = 3.08, SD = 1.390) in the third rank. These findings emphasise the importance of addressing technical and operational readiness.

Other prominent bottlenecks include **limited data accessibility (TB3)** (Mean = 3.03, SD = 1.459, 4th) and **financial constraints (RB1)** (Mean = 3.00, SD = 1.398, 5th), indicating that better data infrastructure and funding are required. Barriers such as **infrastructure limitations**

(TB1) (**Mean = 2.94**, SD = 1.438, 6th), **lack of top management support (OB1)** (**Mean = 2.91**, SD = 1.472, 7th), and **resistance to change (OB2)** (**Mean = 2.90**, SD = 1.430, 8th) indicate moderate organisational and cultural barriers. Cultural barriers (OB3) occupied the last ranking (Mean = 2.89, SD = 1.369), though still relevant.

CHAPTER FIVE

DISCUSSION

5.0 Introduction

This section presents a critical discussion of findings in relation to the study objectives by comparing and contrasting with prior and related studies in the literature. The discussion adopts a balanced perspective that examines both the potential benefits and inherent limitations of AI-BDA technologies in HSCs, while applying the theoretical frameworks of Socio-Technical Systems Theory, Resource-Based View Theory, and Resilience Theory to interpret the findings.

5.1 AI-BDA techniques used in HSCs to enhance resilience

The findings provided rich insights into the evolution of AI-BDA techniques in HSCs and the varying levels of adoption by organisations. The four key techniques: Time-Series Forecasting (TSF), Early Warning Systems (EWS), Logistics Optimisation (LO), and Real-Time Monitoring (RTM) showed differing adoption patterns, providing valuable insights into how technological integration into humanitarian work is defined.

The extent of adoption of early warning systems for pre-positioning stock (EWS3) and multi-objective logistics optimisation for resource positioning (LO2) suggests that humanitarian organisations tend toward AI-BDA applications that align with their operational contexts. These findings corroborate those of Hasan et al. (2023) and Ortuño et al. (2021), who found these techniques helpful for crisis management. However, taken together, these examples reveal a more complex reality about how organisations can adopt technology in practice, if we apply the Socio-Technical Systems Theory to examine these findings.

The selective adoption of AIBDA techniques suggests that their successful integration is more than a technical trade-off; it has more to do with how the characteristics of technology fit with the pre-existing structures in an organisation. The Socio-Technical Systems Theory suggest that system performance can only be optimised through the joint optimisation of the social and technical subsystems (Baxter & Sommerville, 2011). The differences in adoption described in this study suggest that humanitarian organisations will naturally select technologies that fit within their existing socio-technical systems rather than seeking out the most up-to-date or theoretically ideal solutions. This selective adoption trajectory, on the other hand, points to a significant limitation in the dialogue about AI-BDA within humanitarian contexts. Although AI-BDA interventions are often portrayed as ideal solutions across multiple contexts and scenarios, interventions still vary depending on organisational readiness and contextual limitations. For example, the degree of adoption for more complex techniques (e.g., AI flood prediction system (EWS2) and disaster risk prediction with machine learning (EWS1)) compared to community preparedness and broader technology adoption illustrates this limitation, as the EWS2 and EWS1 interventions have been validated in the literature on various land stakeholder initiatives (Tomas et al., 2022).

From a Resource-Based View perspective, the differential adoption example suggests that many humanitarian organisations had not developed AI and BDA capabilities as strategic resources that are valuable, rare, inimitable, and non-substitutable. For example, one explanation for the moderate adoption of real-time monitoring techniques (RTM) is that organisations recognise the utility and added value of RTM, but lack the complementary resources to utilise the technology effectively. This suggests a gap between the perceived potential and actual implementation that is not reflected in the current literature.

The findings also reveal potential negative spillover that are rarely discussed in the predominantly optimistic literature on AI-BDA in humanitarian contexts. The emphasis on sophisticated technological solutions may inadvertently create a digital divide within the humanitarian sector, where well-resourced international organisations gain significant advantages over local humanitarian actors who lack the technical infrastructure and expertise. This technological stratification could undermine the collaborative nature of humanitarian response and potentially marginalise local knowledge and community-based solutions.

Moreover, the focus on data-driven decision-making inherent in AI-BDA systems may gradually erode the intuitive and experiential knowledge that has traditionally guided humanitarian response. While predictive analytics and optimisation algorithms can enhance efficiency, they may also reduce the flexibility and adaptability that are crucial in rapidly changing crises. This represents a fundamental tension between technological optimisation and humanitarian responsiveness that requires careful consideration.

5.2 Effects of AI-BDA techniques on HSCR

The regression analysis demonstrated that AI-BDA techniques significantly enhance HSCR, with the model explaining 84.4% of resilience variance. While this finding appears to strongly support the positive impact of these technologies, a more critical examination reveals important nuances that challenge the prevailing optimistic narrative about AI-BDA as a panacea for humanitarian supply chain challenges.

When interpreted through Resilience Theory, the strong statistical relationship between AI-BDA and resilience suggests that these technologies enhance the three critical aspects of resilience: anticipation through predictive analytics, adaptation through real-time optimization, and recovery through coordinated response mechanisms (Holling, 1973; Walker et al., 2004). However, Resilience Theory also emphasizes the importance of adaptive capacity and learning from experience. The high reliance on AI-BDA systems may actually undermine these capabilities by creating technological dependencies that reduce organizational flexibility and learning capacity.

The study found that Time-Series Forecasting and Logistics Optimization had the strongest effects on resilience, which aligns with previous research by Dubey et al. (2022) and Queiroz and Pereira (2020). However, this finding reveals a concerning bias toward efficiency-oriented measures of resilience that may not capture the full complexity of humanitarian contexts. Traditional resilience metrics often focus on operational efficiency and cost-effectiveness, but humanitarian resilience must also consider factors such as equity, dignity, and community empowerment that are difficult to quantify and may not be enhanced by AI-BDA systems.

The contradiction between the proven effectiveness of certain AI-BDA techniques in literature and their lower adoption rates in practice requires deeper theoretical analysis. From a Socio-Technical Systems perspective, this discrepancy suggests that technical effectiveness alone is insufficient for successful implementation. The social subsystem – including organizational culture, staff capabilities, and stakeholder relationships – must be equally developed for technologies to achieve their potential impact.

This contradiction also highlights a fundamental limitation in how AI-BDA effectiveness is typically measured and reported in academic literature. Most studies focus on technical performance metrics under controlled conditions, but fail to account for the complex organizational and contextual factors that influence real-world implementation. The Resource-Based View Theory provides insight into this phenomenon by suggesting that organizations may rationally choose not to implement technically superior solutions if they cannot develop the complementary resources and capabilities needed to gain sustainable advantage from these technologies.

The findings reveal several critical spillovers that challenge the predominantly positive narrative around AI-BDA in humanitarian contexts. The emphasis on predictive analytics and optimization may lead to over-reliance on algorithmic decision-making, potentially reducing human agency and professional judgment in crisis response. This technological determinism could have serious consequences in humanitarian contexts where cultural sensitivity, ethical considerations, and community participation are essential for effective response.

Furthermore, the substantial investment required for AI-BDA implementation may divert resources from fundamental humanitarian needs such as basic infrastructure, staff training, and community engagement. This resource allocation dilemma represents a significant opportunity cost that is rarely acknowledged in discussions about AI-BDA benefits. Organizations may find themselves in a position where they have sophisticated technological capabilities but lack the basic operational capacity to deliver effective humanitarian assistance.

The study also reveals concerns about algorithmic bias and fairness that have profound implications for humanitarian operations. AI systems trained on historical data may perpetuate or amplify existing inequalities in aid distribution, potentially disadvantaging already marginalized populations. The optimization algorithms that appear to enhance supply chain efficiency may inadvertently reinforce systematic biases that conflict with humanitarian principles of impartiality and non-discrimination.

5.3 Barriers to adopting and implementing AI-BDA within HSCs

The exploratory factor analysis identified three broad categories of barriers: technical, organizational, and resource-related. While this classification is consistent with previous studies (Raut et al., 2021; Moktadir et al., 2019), the specific pattern of barriers observed in humanitarian contexts reveals important insights about the unique challenges facing this sector.

The prominence of skill gaps among staff and lack of technical expertise as the primary barriers reflects a fundamental misalignment between the technical complexity of AI-BDA systems and the human capital available in many humanitarian organizations. From a Socio-Technical Systems perspective, this finding suggests that the technical subsystem has evolved more rapidly than the social subsystem, creating an imbalance that impedes effective implementation. This technical-social gap represents more than just a training issue; it reflects deeper structural challenges in how humanitarian organizations recruit, develop, and retain technical talent.

The finding that organizational barriers such as lack of top management support were less prominent than technical and resource barriers contradicts some literature that emphasizes organizational culture as a key factor in technology adoption (Raut et al., 2021; Shrivastav, 2021). This contradiction can be explained through the unique characteristics of HSCs, which operate under constant time pressure and resource constraints. In such contexts, immediate technical and resource challenges may overshadow longer-term organizational development considerations.

However, this prioritization of technical over organizational barriers may itself represent a significant shortcoming in how humanitarian organizations approach AI-BDA implementation. The Resource-Based View Theory suggests that sustainable competitive advantage comes from resources that are not easily imitated or substituted. While technical capabilities can be acquired relatively quickly, the organizational capabilities needed to effectively leverage AI-BDA – such as data governance, algorithmic accountability, and ethical decision-making frameworks – require longer-term development and may be more crucial for sustained success.

The study identified data integration complexity and limited data accessibility as significant technical barriers, which aligns with findings by Kabra et al. (2023). However, these technical challenges mask deeper issues about data ownership, privacy, and sovereignty that have profound ethical implications. The emphasis on data collection and integration may inadvertently contribute to what some scholars’ term "data colonialism," where external organizations extract and analyze data about vulnerable populations without meaningful participation or benefit-sharing.

Financial constraints emerged as a major resource barrier, reflecting the chronic underfunding that characterizes much of the humanitarian sector. However, the focus on financial barriers may obscure more fundamental questions about resource allocation and priorities. The substantial investments required for AI-BDA implementation must be weighed against competing needs for basic humanitarian services, raising difficult questions about whether these technologies represent the most effective use of limited resources.

The relatively lower ranking of cultural barriers is particularly noteworthy and may reflect a limitation in how barriers are conceptualized and measured. Cultural considerations in humanitarian contexts extend beyond organizational culture to include respect for local customs, traditional knowledge systems, and community participation in decision-making. The implementation of AI-BDA systems may inadvertently marginalize these cultural dimensions, even if they are not explicitly identified as barriers by organizational leaders.

5.4 Research Contributions

The empirical contributions of this study include providing quantitative evidence for the differential effects of specific AI-BDA techniques on HSCR. Unlike previous studies that treat AI-BDA as a monolithic concept, this research disaggregates individual techniques and examines their unique contributions to resilience outcomes. This disaggregated approach reveals important insights about which technologies are most effective and why certain techniques face greater implementation barriers than others.

The study also contributes comparative evidence from Ghana and South Africa, revealing how different institutional and economic contexts influence AI-BDA adoption patterns. This cross-national comparison provides insights into the contextual factors that facilitate or impede technology adoption in developing country contexts, contributing to a more nuanced understanding of how global technologies are adapted to local conditions.

The identification and validation of barrier categories specific to humanitarian contexts represents another important empirical contribution. The finding that resource and technical barriers are more prominent than organizational barriers in humanitarian contexts challenges assumptions derived from commercial sector studies and highlights the need for context-specific approaches to technology implementation.

5.5 Practical Contributions

The practical contributions of this study include providing humanitarian organizations with a framework for assessing their readiness for AI-BDA implementation. The socio-technical alignment framework derived from the findings can help organizations evaluate whether their social and technical subsystems are sufficiently developed to support successful technology adoption.

The barrier prioritization matrix developed from the research provides evidence-based guidance for organizations seeking to overcome implementation challenges. The finding that skill development and technical capacity building should precede organizational change initiatives provides practical direction for sequencing implementation efforts.

The study also contributes to policy discussions by highlighting the need for humanitarian funding models that support long-term technology development rather than short-term project implementation. The findings suggest that traditional project-based funding approaches may be inadequate for supporting the sustained investments required for effective AI-BDA implementation.

The research also provides guidance for technology providers seeking to develop solutions for humanitarian contexts. The emphasis on socio-technical alignment and ethical considerations suggests that successful humanitarian technologies must be designed with explicit attention to organizational capacity, cultural sensitivity, and value alignment rather than focusing solely on technical functionality.

This comprehensive analysis reveals that while AI-BDA technologies offer significant potential for enhancing HSCR, their implementation is far more complex and challenging than current literature suggests. The predominantly optimistic narrative around these technologies must be balanced with recognition of their limitations, potential negative consequences, and the substantial organizational and social changes required for successful implementation. Only through such a balanced and critical perspective can the humanitarian sector make informed decisions about how and when to adopt these powerful but complex technologies.

CHAPTER SIX

CONCLUSIONS AND RECOMMENDATIONS

6.0 Introduction

Given the increasing frequency and complexity of global humanitarian crises, there is an urgent need to enhance the resilience and effectiveness of HSCs. As highlighted in the literature, while AI-BDA show significant potential for strengthening humanitarian operations, their adoption remains limited and under-researched.

In this chapter, the study conclusions and recommendations are presented based on the research findings. The chapter begins by synthesizing the key findings for each research objective regarding AI-BDA implementation in HSCs. Building on these findings, it then provides actionable recommendations for implementing AI-BDA to improve HSCR. The chapter also concludes with suggestions for further research to advance understanding of how AI-BDA can be effectively leveraged in HSCs.

6.1 Conclusions

This research aimed to find the synergy between AI-BDA to improve the resilience of HSCs. By examining the current AI-BDA techniques and their effects and adoption challenges, the study sheds light on the current potential of these technologies in humanitarian contexts.

For the first objective, four predominant AI-BDA techniques were discovered from literature in HSCs: Time-Series Forecasting (TSF), Early Warning Systems (EWS), Logistics Optimization (LO) and Real-Time Monitoring (RTM). Time-series forecasting enables precise planning by using historical information to anticipate future demands, especially during dynamic humanitarian emergencies. Early warning systems leverage machine-learning algorithms to anticipate natural disasters and help plan for the future, lowering the response time and optimising the use of resources. AI-powered logistics optimisation increases transportation and distribution efficiency and delivers timely aid to those in need. In real-time monitoring, backed by RFID and Wi-Fi, inventory and resources can be tracked in real-time, leading to transparency and agility. Together, these technologies highlight a transformation from reactive to predictive and anticipatory methods and drive a massive upgrade in HSC performance. With the help of unifying disconnected data sets, AI and BDA enable holistic situational awareness, crucial for making the right decisions in a time-critical humanitarian situation.

The adoption levels of these techniques varied, with EWS for preparing supplies and LO for resource allocation being the most widely used. However, the lower adoption of techniques such as AI-based flood forecasting systems and machine learning for disaster risk prediction also raises concerns that there might be some obstacles to deployment, including data availability, technical expertise, and organisational readiness. The results also show some lack of standardisation and scalability for these techniques. Although promising, most of their implementation are still pilot initiatives or specific use cases, demonstrating the need for broader adoption and implementation across various humanitarian environments. This requires further infrastructure investments and building models that can generalise the successful application of AI and BDA techniques.

The second objective focused on the effects of AI-BDA techniques on HSCR. The research emphasises the practical value of AI and BDA in strengthening HSCs. Resilience, the ability to predict, change, and recover from events, is greatly enhanced by the predictive and analytical features of AI-BDA. For example, predictive analytics helps humanitarian agencies predict disruptions and take steps to reduce the damage. This is particularly apparent regarding demand prediction models, which optimise resource use and minimise waste.

Integrating BDA provides visibility into supply chains, allowing organisations to discover bottlenecks and drive efficiency in real-time. The ability to analyse massive amounts of data from satellite images, social media and ground sensors allows for a complete assessment of disaster events and quick and accurate decision-making. Further increasing coordination and efficiencies are delivered by AI decision support systems that focus the resources where they are most needed.

Furthermore, AI and BDA play a role in facilitating the cooperation of HSC stakeholders. These technologies provide an avenue for data exchange and communication, promoting trust and coordination among governments, NGOs and corporations. Together, this approach improves disaster response and enhances the adaptive resilience of supply chains for future events.

The regression analysis indicated a positive and significant positive relationship between AI-BDA techniques and HSC resilience, and AI-BDA techniques accounted for 84.4% of the resilience variation. However, technical constraints, such as data quality problems and algorithmic biases, can reduce the AI-BDA system's accuracy and reliability. Additionally, the high costs of deploying these technologies can make them impractical for smaller humanitarian agencies. Despite these obstacles, there is evidence that AI and BDA have a promising future in enhancing the resilience of HSCs, provided that these barriers are addressed.

Finally, the study also identified and revealed the barriers to embracing and utilising AI-BDA in HSCs. According to the exploratory factor analysis, these challenges were classified into technical, organisational, and resource-related barriers. These technical barriers are data quality, interoperability and stability of AI algorithms in unpredictable and unstable situations such as humanitarian emergencies. The fragmented data sources and the absence of consistent data collection and sharing protocols exacerbate these issues. In addition, privacy and security are significant concerns that stand in the way, especially regarding sensitive data. Organisational barriers are equally substantial. Many humanitarian organisations lack the technical resources and infrastructure to deploy and operate AI-BDA platforms. Change resistance and a lack of an enabler organisational culture further hold back adopting these technologies. The research also identifies a lack of leadership commitment and strategic vision, which are key to facilitating technological innovation in HSCs. Resource barriers are among the most ubiquitous. The upfront costs for purchasing, installing and maintaining AI-BDA systems can be prohibitive, particularly for budget-limited humanitarian organisations. Limited funding and other priorities lead to a lack of investment in technological innovations that can help improve operational efficiency and resilience.

Skill gaps among staff and lack of technical expertise emerged as the top-ranked barriers, highlighting the importance of human capital development and capacity building. Additional significant barriers included data integration complexity, limited data accessibility and cost constraints, which suggested a need for better data infrastructure and resources. These challenges demand collaborative efforts from many stakeholders. Governments and foreign institutions must be key players in ensuring funding and policy support for HSC adoption of AI and BDA. The need for capacity-building programs to give humanitarian agencies the necessary skills and knowledge to use these technologies is critical. Engaging with the private sector can also help gain access to innovative technologies and expertise to bridge the resource gap.

6.2 Recommendations

Given the results of this research on AI-BDA in HSCs, the following recommendations are proposed for implementing these technologies to improve resilience in future crises:

1. Given the lower adoption rates of real-time monitoring despite its proven effectiveness, humanitarian organizations 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 crisis situations. Organizations should focus on solutions that overcome connectivity 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, organizations 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 organizational readiness. Partnerships with academic institutions and technology companies can facilitate knowledge transfer, while creating communities of practice across humanitarian agencies will support shared learning and standardization of AI-BDA implementation approaches.

3. To maximize AI-BDA's impact on supply chain resilience while addressing ethical concerns, humanitarian organizations 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 marginalized communities rather than reinforcing existing inequalities.

4. Given the challenges related to data accessibility and integration complexity, it is essential to develop robust data governance frameworks. Governments and humanitarian agencies should establish standardised data-sharing protocols that enable seamless interoperability

across different organisations and platforms. Investing in cloud-based systems and blockchain technology can enhance real-time data access, security, and collaboration among humanitarian stakeholders, ultimately improving AI-BDA implementation in supply chain operations.

5. Policymakers in Ghana and South Africa should develop targeted funding initiatives to support AI-BDA integration in HSCs. This could include tax incentives, grants, or public-private partnerships aimed at reducing financial constraints associated with AI adoption. Additionally, regulatory bodies should create AI-friendly policies that encourage ethical and inclusive AI applications in humanitarian operations, ensuring alignment with global best practices while addressing the unique challenges faced in African humanitarian contexts.

6.3 Limitations of the study

While this study provides valuable insights into integrating AI and BDA in HSCs, it has limitations. First, the study was conducted on humanitarian organisations in Ghana and South Africa, which might limit the applicability of the results to other geographical areas. Second, the study employed a purposive sampling technique that could introduce participant selection bias. Third, the cross-sectional research collected information at a single time, which may not represent the dynamic nature of AI-BDA in HSCs.

Furthermore, the study used quantitative methods, which may not provide a deep understanding of the complex social, organizational, and cultural factors influencing AI-BDA implementation. Qualitative data could have been more enriching and helped comprehensively understand these technologies' challenges and prospects.

Lastly, the research reflected the opinions of humanitarian professionals and not affected people or other stakeholders like technology providers and policymakers. Bringing such a diverse perspective to the discourse could have provided a more holistic understanding of the ethical implications and social impact of AI-BDA in humanitarian contexts.

6.4 Suggestions for further research

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

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 HSCs.

3. Utilise mixed methods, including quantitative and qualitative, to holistically explore the social, organisational and cultural dimensions of AI-BDA implementation.

4. Explore affected communities and other stakeholders' perspectives and experiences to evaluate the ethics and social impact of AI-BDA in humanitarian scenarios.

5. Develop and validate frameworks and models for responsible, inclusive deployment of AI-BDA in HSCs, considering the unique challenges and ethical considerations of these contexts.

References

Abhulimen, A. O., & Ejike, O. G. (2024). Solving supply chain management issues with AI and Big Data analytics for future operational efficiency. *Computer Science & IT Research Journal*, *5*(8), 1780-1805.

Abid, S. K., Sulaiman, N., Chan, S. W., Nazir, U., Abid, M., Han, H., ... & Vega-Muñoz, A. (2021). Toward an integrated disaster management approach: how artificial intelligence can boost disaster management. *Sustainability*, *13*(22), 12560.

Adrian, C., Abdullah, R., Atan, R., & Jusoh, Y. Y. (2018, March). Expert review on big data analytics implementation model in data-driven decision-making. In *2018 Fourth International Conference on Information Retrieval and Knowledge Management (CAMP)* (pp. 1-5). IEEE.

Agarwal, S., Kant, R., & Shankar, R. (2020). Evaluating solutions to overcome humanitarian supply chain management barriers: A hybrid fuzzy SWARA–Fuzzy WASPAS approach. *International Journal of Disaster Risk Reduction*, *51*, 101838.

Aggarwal, C. C., & Yu, P. S. (2001, May). Outlier detection for high dimensional data. In *Proceedings of the 2001 ACM SIGMOD international conference on Management of data* (pp. 37-46). https://doi.org/10.35940/ijeat.e2675.0610521

Ahmadi, S. (2024). A Comprehensive Study on Integration of Big Data and AI in Financial Industry and its Effect on Present and Future Opportunities. *International Journal of Current Science Research and Review,* *07*(01), 66–74. https://doi.org/10.47191/ijcsrr/V7-i1-07

AlAnazi, A. A., Shamsudin, F. M., & Johari, J. (2016). Linking organisational culture, leadership styles, human resource management practices and organisational performance: Data screening and preliminary analysis. *American Journal of Management*, *16*(1).

Albergaria, R., Bandeira, D. M., Silva, L. D. O., Paula, A. De, & Bandeira, F. (2021). Planning the use of helicopters for supply distribution in response operations to sudden disasters. *Gestão & Produção, 28*(1), 1–19.

Ali, A., Mahfouz, A., & Arisha, A. (2017). Analysing supply chain resilience: integrating the constructs in a concept mapping framework via a systematic literature review. *Supply chain management: an international journal*, *22*(1), 16-39.

Ali, A., Sharabati, A., Alqurashi, D., Shkeer, A., & Allahha, M. (2024). The impact of artificial intelligence and supply chain collaboration on supply chain resilience: Mediating the effects of information sharing. *Uncertain Supply Chain Management*, *12*(3), 1801-1812.

Aljabhan, B., & Abeyie, M. (2022). Big data analytics in supply chain management: A qualitative study. *Computational Intelligence and Neuroscience*, *2022*(1), 9573669.

Aljohani, A. (2023). Predictive analytics and machine learning for real-time supply chain risk mitigation and agility. *Sustainability*, *15*(20), 15088.

Altay, N., & Narayanan, A. (2020). Forecasting in humanitarian operations: Literature review and research needs. *International Journal of Forecasting, 38*. https://doi.org/10.1016/j.ijforecast.2020.08.001

Alturki, I., & Lee, S. (2024). The humanitarian vehicle routing problem with non-routineness of trips. *Socio-Economic Planning Sciences*, *92*, 101838. https://doi.org/10.1016/j.seps.2024.101838

Ames, H., Glenton, C., & Lewin, S. (2019). Purposive sampling in a qualitative evidence synthesis: A worked example from a synthesis on parental perceptions of vaccination communication. *BMC medical research methodology*, *19*, 1-9.

Anjomshoae, A., Banomyong, R., Azadnia, A. H., Kunz, N., Anjomshoae, A., Banomyong, R., & Azadnia, A. H. (2023). Sustainable humanitarian supply chains : a systematic literature review and research propositions. *Production Planning & Control*, 1–21. https://doi.org/10.1080/09537287.2023.2273451

Ara, S., Akib, M. M. M. K., Oion, M. S. R., Shohel, M. H. R., Ridoy, M. N. F., Kabita, F. A., & Shahiduzzaman, M. (2023, December). Vehicle Routing Problem Solving Using Reinforcement Learning. In *2023 26th International Conference on Computer and Information Technology (ICCIT)* (pp. 1-6). IEEE.

Argollo da Costa, S. R., Bandeira, R., Mello, L., & Campos, V. (2014). Humanitarian supply chain: An analysis of response operations to natural disasters*. European Journal of Transport and Infrastructure Research, 14*, 290–310. https://doi.org/10.18757/ejtir.2014.14.3.3035

Azmat, M., & Kummer, S. (2020). Potential applications of unmanned ground and aerial vehicles to mitigate challenges of transport and logistics-related critical success factors in the humanitarian supply chain. *Asian journal of sustainability and social responsibility*, *5*(1), 3.

Babbie, E. (2017). *The practice of social research* (14th ed.). Cengage Learning.

Bag, S., Dhamija, P., Luthra, S., & Huisingh, D. (2023). How big data analytics can help manufacturing companies strengthen supply chain resilience in the context of the COVID-19 pandemic. *The International Journal of Logistics Management*, *34*(4), 1141-1164.

Bag, S., Dhamija, P., Luthra, S., & Huisingh, D. (2023). How big data analytics can help manufacturing companies strengthen supply chain resilience in the context of the COVID-19 pandemic. *The International Journal of Logistics Management*, *34*(4), 1141-1164.

Bag, S., Gupta, S., & Wood, L. (2022). Big data analytics in sustainable humanitarian supply chain: Barriers and their interactions. *Annals of Operations Research*, *319*(1), 721-760.

Bag, S., Wood, L. C., Xu, L., Dhamija, P., & Kayikci, Y. (2020). Big data analytics as an operational excellence approach to enhance sustainable supply chain performance. *Resources, conservation and recycling*, *153*, 104559. https://doi.org/10.1016/j.resconrec.2019.104559

Baharmand, H., Maghsoudi, A., & Coppi, G. (2021). Exploring the application of blockchain to humanitarian supply chains: insights from Humanitarian Supply Blockchain pilot project. *International Journal of Operations & Production Management*, *41*(9), 1522-1543.

Balcik, B., Bozkir, C. D. C., & Kundakcioglu, O. E. (2016). A literature review on inventory management in humanitarian supply chains. *Surveys in Operations Research and Management Science,* *21*(2), 101–116. https://doi.org/https://doi.org/10.1016/j.sorms.2016.10.002

Bányai, T. (2022, March). Impact of digital twin technology on the real-time optimisation of material handling processes. In *IOP Conference Series: Materials Science and Engineering* (Vol. 1235, No. 1, p. 012077). IOP Publishing.

Bari, L. F., Ahmed, I., Ahamed, R., Zihan, T. A., Sharmin, S., Pranto, A. H., & Islam, M. R. (2023). Potential Use of Artificial Intelligence (AI) in Disaster Risk and Emergency Health Management: A Critical Appraisal on Environmental Health. *Environmental*

Health Insights, 17, 11786302231217808. https://doi.org/10.1177/11786302231217808

Barney, J. (1991). Firm resources and sustained competitive advantage. *Journal of management*, *17*(1), 99-120. https://doi.org/10.1177/014920639101700108

Bastani, P., Rouhollahi, N., & Tahernejad, A. (2015). Validity and reliability of TeachersEvaluation questionnaires from students' point of view in Tehran University of Medical Sciences. *Medical Education Journal*, *3*(1), 7-14.

Baxter, G., & Sommerville, I. (2011). Socio-technical systems: From design methods to systems engineering. *Interacting with computers*, *23*(1), 4-17.

Beduschi, A. (2022). Harnessing the potential of artificial intelligence for humanitarian action: Opportunities and risks. *International Review of the Red Cross, 104*(919), 1149-1169. https://doi.org/10.1017/S1816383122000261

Beduschi, A. (2022). Harnessing the potential of artificial intelligence for humanitarian action: Opportunities and risks. *International Review of the Red Cross, 104*(919), 1149–1169. https://doi.org/10.1017/S1816383122000261

Behl, A., & Dutta, P. (2019). Humanitarian supply chain management: a thematic literature review and future directions of research. *Annals of Operations Research, 283*(1), 1001-1044.

Belhadi, A., Mani, V., Kamble, S. S., Khan, S. A. R., & Verma, S. (2024). Artificial intelligence-driven innovation for enhancing supply chain resilience and performance under the effect of supply chain dynamism: an empirical investigation. *Annals of Operations Research*, *333*(2), 627–652.

Bhattacharya, S., Hasija, S., & Van Wassenhove, L. N. (2014). Designing efficient infrastructural investment and asset transfer mechanisms in humanitarian supply chains. *Production and Operations Management*, *23*(9), 1511-1521.

Blackhurst, J., Dunn, K. S., & Craighead, C. W. (2011). An empirically derived framework of global supply resiliency. *Journal of business logistics*, *32*(4), 374-391. https://doi.org/10.1111/j.0000-0000.2011.01032.x

Blank, M. (2021). *Maritime transportation in humanitarian logistics: the case of Yemen crisis* (Master's thesis, Hanken School of Economics). https://helda.helsinki.fi/server/api/core/bitstreams/dc5493c7-eeb1-4dc3-91d5-bb1b8db6828a/content

Boafo, Y. A., Saito, O., Jasaw, G. S., Yiran, G. A., Lam, R. D., Mohan, G., & Kranjac-Berisavljevic, G. (2020). Perceived community resilience to floods and droughts induced by climate change in semi-arid Ghana. *Sustainability Challenges in Sub-Saharan Africa I: Continental Perspectives and Insights from Western and Central Africa*, 191-219.

Budak, A., Kaya, I., Karaşan, A., & Erdoğan, M. (2020). Real-time location systems selection by using a fuzzy MCDM approach: An application in humanitarian relief logistics. Applied Soft Computing, 92, 106322.

Burnard, K., Bhamra, R., & Tsinopoulos, C. (2018). Building organizational resilience: Four configurations. *IEEE transactions on engineering management*, *65*(3), 351-362.

Cai, L., & Zhu, Y. (2015). The challenges of data quality and data quality assessment in the big data era. Data Science Journal, 14, 1–10. https://doi.org/10.5334/dsj-2015-002

Carratù, M., Gallo, V., Paciello, V., & Pietrosanto, A. (2022, May). A deep learning approach for the development of an Early Earthquake Warning system. In *2022 IEEE International Instrumentation and Measurement Technology Conference (I2MTC)* (pp. 1-6). IEEE.

Chan, E. Y. (2006). Evidence-based public health practices: challenges for health needs assessments in disasters. *Hong Kong Medical Journal*, *12*(4), 324.

Chan, F. T., Samvedi, A., & Chung, S. H. (2015). Fuzzy time series forecasting for supply chain disruptions. *Industrial Management & Data Systems*, *115*(3), 419-435.

Charles, A., Lauras, M., Van Wassenhove, L. N., & Dupont, L. (2016). Designing an efficient humanitarian supply network. *Journal of Operations Management*, *47*, 58-70.

Chen, F., Liu, S., & Appolloni, A. (2020). Horizontal coordination of I-LNGOs in the humanitarian supply chain: an evolutionary game approach. *Sustainability*, *12*(15), 5953.

Cherns, A. (1976). The principles of sociotechnical design. *Human relations*, *29*(8), 783-792.

Choi, T. M., Dolgui, A., Ivanov, D., & Pesch, E. (2022). OR and analytics for digital, resilient, and sustainable manufacturing 4.0. *Annals of Operations Research*, *310*(1), 1-6.

Chowdhury, M. M. H., & Quaddus, M. (2016). Supply chain readiness, response and recovery for resilience. *Supply Chain Management: An International Journal*, *21*(6), 709-731.

Chowdhury, M. M. H., Chowdhury, P., Quaddus, M., Rahman, K. W., & Shahriar, S. (2024). Flexibility in Enhancing Supply Chain Resilience: Developing a Resilience Capability Portfolio in the Event of Severe Disruption. *Global Journal of Flexible Systems Management, 25*(2), 395–417. https://doi.org/10.1007/s40171-024-00391-2

Cisterna, D., Seibel, S., Oprach, S., & Haghsheno, S. (2022). Artificial Intelligence for the Construction Industry Statistical Descriptive Analysis of Drivers and Barriers. In *New Trends in Disruptive Technologies, Tech Ethics and Artificial Intelligence: The DITTET Collection 1* (pp. 283-295). Springer International Publishing.

Clegg, C. W. (2000). Sociotechnical principles for system design. *Applied ergonomics*, *31*(5), 463-477.

Comes, T. (2016). Designing for networked community resilience. *Procedia engineering*, *159*, 6-11.

Conway, J. M., & Huffcutt, A. I. (2003). A review and evaluation of exploratory factor analysis practices in organisational research. *Organisational research methods*, *6*(2), 147–168.

Creswell, J. W., & Creswell, J. D. (2018). *Research design: Qualitative, quantitative, and mixed methods approaches* (5th ed.). Sage Publications.

Davis, M. C., Challenger, R., Jayewardene, D. N., & Clegg, C. W. (2014). Advancing socio-technical systems thinking: A call for bravery. *Applied ergonomics*, *45*(2), 171-180.

Day, J. M., Melnyk, S. A., Larson, P. D., Davis, E. W., & Whybark, D. C. (2012). Humanitarian and disaster relief supply chains: a matter of life and death. *Journal of Supply Chain Management*, *48*(2), 21-36. https://doi.org/10.1111/j.1745-493X.2012.03267.x

de Camargo Fiorini, P., Chiappetta Jabbour, C. J., Lopes de Sousa Jabbour, A. B., & Ramsden, G. (2022). The human side of humanitarian supply chains: a research agenda and systematization framework. *Annals of Operations Research*, *319*(1), 911-936.

de la Fuente, A., Meruane, V., & Meruane, C. (2019). Hydrological early warning system based on a deep learning runoff model coupled with a meteorological forecast. *Water*, *11*(9), 1808.

de Vries, H. (2017). *Evidence-based optimization in humanitarian logistics* (No. EPS-2017-435-LIS).

Dehkhodaei, A., Amiri, B., Farsijani, H., & Raad, A. (2023). Barriers to big data analytics (BDA) implementation in manufacturing supply chains. *Journal of Management Analytics*, *10*(1), 191-222.

Dennehy, D., Oredo, J., Spanaki, K., Despoudi, S., & Fitzgibbon, M. (2021). Supply chain resilience in mindful humanitarian aid organizations: the role of big data analytics. *International Journal of Operations & Production Management*, *41*(9), 1417-1441. https://doi.org/10.1108/IJOPM-12-2020-0871

Devitt, S. K., Scholz, J., Schless, T., & Lewis, L. (2023). Developing a trusted human-AI network for humanitarian benefit. *Digital War*, *4*(1), 1-17. https://doi.org/10.1057/s42984-023-00063-y

Diehlmann, F., Lüttenberg, M., Verdonck, L., Wiens, M., Zienau, A., & Schultmann, F. (2021). Public-private collaborations in emergency logistics: A framework based on logistical and game-theoretical concepts. *Safety Science, 141*, 105301. https://doi.org/https://doi.org/10.1016/j.ssci.2021.105301

Dubey, R., Ali, S. S., Aital, P., & Venkatesh, V. G. (2014). Mechanics of humanitarian supply chain agility and resilience and its empirical validation. *International Journal of Services and Operations Management*, *17*(4), 367-384. https://doi.org/10.1504/IJSOM.2014.059999

Dubey, R., Bryde, D. J., Dwivedi, Y. K., Graham, G., & Foropon, C. (2022a). Impact of artificial intelligence-driven big data analytics culture on agility and resilience in humanitarian supply chain: A practice-based view. *International Journal of Production Economics*, *250*, 108618. https://doi.org/10.1016/j.ijpe.2022.108618

Dubey, R., Bryde, D. J., Foropon, C., Graham, G., Giannakis, M., & Mishra, D. B. (2022b). Agility in humanitarian supply chain: An organizational information processing perspective and relational view. *Annals of Operations Research*, *319*(1), 559-579.

Dubey, R., Bryde, D. J., Foropon, C., Tiwari, M., Dwivedi, Y., & Schiffling, S. (2021). An investigation of information alignment and collaboration as complements to supply chain agility in humanitarian supply chain. *International Journal of Production Research*, *59*(5), 1586-1605.

Dubey, R., Gunasekaran, A., Bryde, D. J., Dwivedi, Y. K., & Papadopoulos, T. (2020). Blockchain technology for enhancing swift-trust, collaboration and resilience within a humanitarian supply chain setting. *International journal of Production research*, *58*(11), 3381-3398.

Dubey, R., Gunasekaran, A., Childe, S. J., Fosso Wamba, S., Roubaud, D., & Foropon, C. (2021). Empirical investigation of data analytics capability and organizational flexibility as complements to supply chain resilience. *International Journal of Production Research*, *59*(1), 110-128. https://doi.org/10.1080/00207543.2019.1582820

Dubey, R., Gunasekaran, A., Childe, S. J., Roubaud, D., Fosso Wamba, S., Giannakis, M., & Foropon, C. (2019). Big data analytics and organisational culture as complements to swift trust and collaborative performance in the humanitarian supply chain. *International Journal of Production Economics*, 210, 120–136. https://doi.org/https://doi.org/10.1016/j.ijpe.2019.01.023

Dubey, R., Luo, Z., Gunasekaran, A., Akter, S., Hazen, B. T., & Douglas, M. A. (2018). Big data and predictive analytics in humanitarian supply chains: Enabling visibility and coordination in the presence of swift trust. *The International Journal of Logistics Management*, *29*(2), 485-512.

Eason, K. (2014). Afterword: The past, present and future of sociotechnical systems theory. *Applied ergonomics*, *45*(2), 213-220.

Ejjami, R., & Boussalham, K. (2024). Resilient Supply Chains in Industry 5.0: Leveraging AI for Predictive Maintenance and Risk Mitigation. *IJFMR-Int J Multidiscip Res [Internet]*, *6*(4). https://doi.org/10.36948/ijfmr.2024.v06i04.25116

Elufioye, O. A., Ike, C. U., Odeyemi, O., Usman, F. O., & Mhlongo, N. Z. (2024). Ai-Driven predictive analytics in agricultural supply chains: a review: assessing the benefits and challenges of ai in forecasting demand and optimizing supply in agriculture. *Computer Science & IT Research Journal*, *5*(2), 473-497.

Emrouznejad, A., Abbasi, S., & Sıcakyüz, Ç. (2023). Supply chain risk management: A content analysis-based review of existing and emerging topics. *Supply Chain Analytics, 3*, 100031. https://doi.org/https://doi.org/10.1016/j.sca.2023.100031

Esposito, M., Palma, L., Belli, A., Sabbatini, L., & Pierleoni, P. (2022). Recent advances in internet of things solutions for early warning systems: A review. *Sensors*, *22*(6), 2124.

Fan, C., Zhang, C., Yahja, A., & Mostafavi, A. (2021). Disaster City Digital Twin: A vision for integrating artificial and human intelligence for disaster management. *International journal of information management*, *56*, 102049. https://doi.org/10.1016/j.ijinfomgt.2019.102049

Fathalikhani, S., Hafezalkotob, A., & Soltani, R. (2020). Government intervention on cooperation, competition, and coopetition of humanitarian supply chains. *Socio-Economic Planning Sciences*, *69*, 100715.

Fellows, R.F., & Liu, A.M. (2015). *Research Methods for Construction*. John Wiley and Sons.

Fife, S. T., & Gossner, J. D. (2024). Deductive qualitative analysis: Evaluating, expanding, and refining theory. *Qualitative Health Research*, 34(8), 1124-1137.

Firman, F., Anra, Y., Pratama, R., & Wulan Tersta, F. (2021). Factors Affecting Intentions and Behavior of Plagiarism Among Students in Jambi University: Testing the Data Quality for Validity and Reliability. *SPEKTRUM Jurnal Pendidikan Luar Sekolah (PLS)*, *9*(4), 462-478.

Folke, C., Carpenter, S. R., Walker, B., Scheffer, M., Chapin, T., & Rockström, J. (2010). Resilience thinking: integrating resilience, adaptability and transformability. *Ecology and society*, *15*(4). http://www.ecologyandsociety.org/vol15/iss4/art20/

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of marketing research*, *18*(1), 39-50.

Fuqua, D., & Hespeler, S. (2022). Commodity demand forecasting using modulated rank reduction for humanitarian logistics planning. *Expert Systems with Applications*, *206*, 117753.

Ghadge, A. (2023). ICT-enabled approach for humanitarian disaster management: a systems perspective. *The International Journal of Logistics Management*, *34*(6), 1543-1565. https://doi.org/10.1108/IJLM-11-2021-0532

Gillespie, J. (2023). Integrating data-driven risk mitigation into supply chain planning and management. *Journal of Supply Chain Management, Logistics and Procurement*, *6*(1), 35-44.

Grant, R. M. (1996). Toward a knowledge-based theory of the firm. *Strategic management journal*, *17*(S2), 109-122. https://doi.org/10.1002/smj.4250171110

Gupta, S., Altay, N., & Luo, Z. (2019). Big data in humanitarian supply chain management: A review and further research directions. *Annals of Operations Research*, *283*(1), 1153-1173.

Gupta, S., Modgil, S., Gunasekaran, A., & Bag, S. (2020, July). Dynamic capabilities and institutional theories for Industry 4.0 and digital supply chain. In *Supply Chain Forum: An International Journal* (Vol. 21, No. 3, pp. 139-157). Taylor & Francis. https://doi.org/10.1108/IJLM-02-2021-0094

Gupta, S., Starr, M. K., Farahani, R. Z., & Matinrad, N. (2016). Disaster management from a POM perspective: Mapping a new domain. *Production and Operations Management*, *25*(10), 1611-1637.

Haig, B. D. (2005). An abductive theory of scientific method. *Psychological Methods*, 10(4), 371-388.

Harish, R., Harish R.D., Kalaiselvi, D.K.R, Hari H.V. (2023). Arduino Child Caring Robot. *International Journal for Research in Applied Science and Engineering Technology*, 11 (6), 3915 – 3917. https://doi.org/10.22214/ijraset.2023.51908

Hart, P. D. (2019). Construct Validity Evidence for the Muscle Strengthening Activity Scale (MSAS). *American Journal of Public Health Research*, *7*(5), 189–193.

Hart, S. L. (1995). A natural-resource-based view of the firm. *Academy of management review*, *20*(4), 986-1014. https://doi.org/10.5465/amr.1995.9512280033

Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the academy of marketing science*, *43*, 115-135.

Hitt, M. A., Xu, K., & Carnes, C. M. (2016). Resource based theory in operations management research. *Journal of operations management*, *41*, 77-94. https://doi.org/10.1016/j.jom.2015.11.002

Holguín-Veras, J., Jaller, M., Van Wassenhove, L. N., Pérez, N., & Wachtendorf, T. (2012). On the unique features of post-disaster humanitarian logistics. *Journal of Operations Management*, *30*(7-8), 494-506.

Holling, C. S. (1973). *Resilience and stability of ecological systems.* Annual Review of Ecology and Systematics, 4(1), 1-23. https://doi.org/10.1146/annurev.es.04.110173.000245

Hu, S., Dong, Z., & Lev, B. (2022). Supplier selection in disaster operations management: Review and research gap identification. *Socio-Economic Planning Sciences, 82*, 101302. https://doi.org/10.1016/j.seps.2022.101302

Ismail, I. (2021). A possibilistic mathematical programming model to control the flow of relief commodities in humanitarian supply chains. *Computers & Industrial Engineering*, *157*, 107305.

Ivanov, D., & Dolgui, A. (2020). Viability of intertwined supply networks: extending the supply chain resilience angles towards survivability. A position paper motivated by COVID-19 outbreak. *International journal of production research*, *58*(10), 2904-2915.

Jahre, M. (2017). Humanitarian supply chain strategies–a review of how actors mitigate supply chain risks. *Journal of Humanitarian Logistics and Supply Chain Management*, *7*(2), 82-101.

Jahre, M., & Fabbe-Costes, N. (2015). How standards and modularity can improve humanitarian supply chain responsiveness: The case of emergency response units. *Journal of Humanitarian Logistics and Supply Chain Management*, *5*(3), 348-386.

Jahre, M., & Jensen, L.-M. (2010). Coordination in humanitarian logistics through clusters. *International Journal of Physical Distribution & Logistics Management, 40*, 657–674. https://doi.org/10.1108/09600031011079319

Jahre, M., Kembro, J., Rezvanian, T., Ergun, O., Håpnes, S. J., & Berling, P. (2016). Integrating supply chains for emergencies and ongoing operations in UNHCR. *Journal of Operations Management*, *45*, 57-72.

Jain, P., Tambuskar, D. P., & Narwane, V. S. (2023). Is the implementation of big data analytics in sustainable supply chain really a challenge? The context of the Indian manufacturing sector. *International Journal of Innovation and Technology Management, 20*(05), 2350033. https://doi.org/10.1142/s0219877023500335

Jain, P., Tambuskar, D. P., & Narwane, V. S. (2023). Is the implementation of big data analytics in sustainable supply chain really a challenge? The context of the Indian manufacturing sector. *International Journal of Innovation and Technology Management*, *20*(05), 2350033.

Jain, S., Dubey, S., & Jain, S. (2016). Designing and validation of questionnaire. *International dental & medical journal of advanced research*, *2*(1), 1-3.

Janadari, M. P. N., Sri Ramalu, S., Wei, C., & Abdullah, O. Y. (2016, December). Evaluation of measurement and structural model of the reflective model constructs in PLS-SEM. In *Proceedings of the 6th International Symposium—2016 South Eastern University of Sri Lanka (SEUSL), Oluvil, Sri Lanka* (pp. 20-21).

Jha, A. (2024). 4. AI-Driven Algorithms for Optimizing Social Media Advertising. Advances in e-business research series. doi: 10.4018/979-8-3693-1781-5.ch004

Jim, M. M. I., Rauf, M. A., Rahman, M. M., & Tariquzzaman, M. (2024). AI-Powered Predictive Analytics For Intellectual Property Risk Management In Supply Chain Operations: A Big Data Approach. *Available at SSRN 4986872*.

John, L., & Ramesh, A. (2012). Humanitarian supply chain management in India: a SAP-LAP framework. *Journal of advances in management research*, *9*(2), 217-235.

John, L., Gurumurthy, A., Soni, G., & Jain, V. (2019). Modelling the inter-relationship between factors affecting coordination in a humanitarian supply chain: a case of Chennai flood relief. *Annals of Operations Research*, *283*, 1227-1258.

Kabra, G., & Anbanandam, R. (2015). Analysing ICT issues in humanitarian supply chain management: A SAP-LAP linkages framework. *Global Journal of Flexible Systems Management, 16*. https://doi.org/10.1007/s40171-014-0088-3

Kabra, G., Ramesh, A., Jain, V., & Akhtar, P. (2023). Barriers to information and digital technology adoption in humanitarian supply chain management: a fuzzy AHP approach. *Journal of Enterprise Information Management, 36*(2), 505-527. https://doi.org/10.1142/s0219877023500335

Kabra, G., Ramesh, A., Jain, V., & Akhtar, P. (2023). Barriers to information and digital technology adoption in humanitarian supply chain management: a fuzzy AHP approach. *Journal of Enterprise Information Management*, *36*(2), 505-527.

Kahn, L., Ortiz-Ulloa, B., Pavon-Harr, V., & Savas, O. (2019). Artificial Intelligence (AI) Augmentation for Humanitarian Logistics: A Framework and Visual Tool for Planning and Communicating Optimal Evacuation Routes for Natural Hazards.

Kamalahmadi, M., & Parast, M. M. (2016). A review of the literature on the principles of enterprise and supply chain resilience: Major findings and directions for future research. *International journal of production economics*, *171*, 116-133. https://doi.org/10.1016/j.ijpe.2015.10.023

Kassam-Adams, N., Marsac, M. L., Kohser, K. L., Kenardy, J. A., March, S., & Winston, F. K. (2015). A new method for assessing content validity in model-based creation and iteration of eHealth interventions. *Journal of medical Internet research*, *17*(4), e95.

Kılıç, S. (2016). Cronbach's alpha reliability coefficient -. *Journal of Mood Disorders, 6*, 47.

Kitazawa, K., & Hale, S. A. (2021). Social media and early warning systems for natural disasters: A case study of Typhoon Etau in Japan. *International Journal of Disaster Risk Reduction*, *52*, 101926.

Klundert, J.V., Wagelmans, A.P., & Vries, H.D. (2013). Evidence-Based Optimization in Humanitarian Logistics.

Kondraganti, A. (2021). Big Data Analytics in Humanitarian and Disaster Operations: A Systematic Review.

Korteweg, H. A., van Bokhoven, I., Yzermans, C. J., & Grievink, L. (2010). Rapid health and needs assessments after disasters: a systematic review. *BMC public health*, *10*, 1-12.

Kovács, G., & Tatham, P. (2009). Responding to disruptions in the supply network-from dormant to action. *Journal of business logistics*, *30*(2), 215-229. https://doi.org/10.1002/j.2158-1592.2009.tb00121.x

Kraaijenbrink, J., Spender, J. C., & Groen, A. J. (2010). The resource-based view: A review and assessment of its critiques. *Journal of management*, *36*(1), 349-372. https://doi.org/10.1177/0149206309350775

Kreutzer, T., Vinck, P., Pham, P. N., An, A., Appel, L., DeLuca, E., ... & Orbinski, J. (2019). Improving humanitarian needs assessments through natural language processing. *IBM Journal of Research and Development*, *64*(1/2), 9-1.

Kumar, A., Latif, Y. L., & Daver, F. (2012). Developing forecasting tool for humanitarian relief organizations in emergency logistics planning. *World Academy of Science, Engineering and Technology Journal*, 1687-1693November.

Kumar, P., Choubey, D., Amosu, O. R., & Ogunsuji, Y. M. (2024). AI-enhanced inventory and demand forecasting: Using AI to optimize inventory management and predict customer demand. World Journal of Advanced Research and Reviews, 23(1), 1931-1944. doi: 10.30574/wjarr.2024.23.1.2173

Kumar, R. (2019). *Research methodology: A step-by-step guide for beginners* (5th ed.). Sage Publications.

Kundu, A., Gorai, J., & Angadi, G. R. (2024). The development and validation of a tool measuring administrators' attitudes towards the Apprenticeship Embedded Degree Program. *Journal of Applied Research in Higher Education*, *16*(3), 706-720.

Kunz, N., & Gold, S. (2017). Sustainable humanitarian supply chain management–exploring new theory. *International Journal of Logistics Research and Applications*, *20*(2), 85-104.

Kusi-Sarpong, S., Orji, I. J., Gupta, H., & Kunc, M. (2021). Risks associated with the implementation of big data analytics in sustainable supply chains. *Omega*, *105*, 102502.

Kusi-Sarpong, S., Orji, I. J., Gupta, H., & Kunc, M. (2021). Risks associated with the implementation of big data analytics in sustainable supply chains. *Omega, 105*, 102502. https://doi.org/https://doi.org/10.1016/j.omega.2021.102502

L'Hermitte, C., Tatham, P., Brooks, B., & Bowles, M. (2016). Supply chain agility in humanitarian protracted operations. *Journal of Humanitarian Logistics and Supply Chain Management, 6*, 173–201. https://doi.org/10.1108/JHLSCM-09-2015-0037

Laguna Salvadó, L., Lauras, M., & Comes, T. (2016). Towards a monitoring system for American IFRC logistics network. *ISCRAM, Rio de Janeiro*.

Lamenza, A. A. da S., Fontainha, T. C., & Leiras, A. (2019). Purchasing strategies for relief items in humanitarian operations relief items. *Journal of Humanitarian Logistics and Supply Chain Management, 9*(2), 151–171. https://doi.org/10.1108/JHLSCM-09-2018-0060

Lauri, A. De. (2021). Humanitarianism : An Overview. *CMI INSIGHT, 3*, 1–6.

Lenzner, T. (2014). Are readability formulas valid tools for assessing survey question difficulty? *Sociological Methods & Research*, *43*(4), 677–698.

Lewin, A. Y., Chiu, C. Y., Fey, C. F., Levine, S. S., McDermott, G., Murmann, J. P., & Tsang, E. (2016). The critique of empirical social science: New policies at management and organization review. *Management and Organization Review*, *12*(4), 649-658.

Lewin, R., Besiou, M., Lamarche, J. B., Cahill, S., & Guerrero-Garcia, S. (2018). Delivering in a moving world… looking to our supply chains to meet the increasing scale, cost and complexity of humanitarian needs. *Journal of Humanitarian Logistics and Supply Chain Management*, *8*(4), 518-532.

L'Hermitte, C., Brooks, B., Bowles, M., & Tatham, P. H. (2017). Investigating the strategic antecedents of agility in humanitarian logistics. *Disasters*, *41*(4), 672-695.

Li, X., & Lv, Y. (2021, October). Big Data-Driven Disaster Management: A Key Approach for Smart Humanitarian Activity. In *2021 IEEE 21st International Conference on Communication Technology* (ICCT) (pp. 1449-1454). IEEE. https://doi.org/10.1109/ICCT52962.2021.9657900

Lim, W. M. (2025). What is qualitative research? An overview and guidelines. *Australasian Marketing Journal*, *33*(2), 199-229.

Lima, G. R. T. D., & Scofield, G. B. (2021). Feasibility study on operational use of neural networks in a flash flood early warning system. *RBRH*, *26*, e7.

Liu, F., Song, J.-S., & Tong, J. (2016). Building Supply Chain Resilience through Virtual Stockpile Pooling. *Production and Operations Management, 25*. https://doi.org/10.1111/poms.12573

Madianou, M. (2020). *Non-Human Humanitarianism: When AI for Good Turns Out To Be Bad*. AoIR Selected Papers of Internet Research. https://doi.org/10.5210/spir.v2020i0.11267

Madianou, M. (2021). Nonhuman humanitarianism: when'AI for good'can be harmful. *Information, Communication & Society*, *24*(6), 850-868. https://doi.org/10.1080/1369118X.2021.1909100

Maheshwari, S., Gautam, P., & Jaggi, C. K. (2021). Role of Big Data Analytics in supply chain management: current trends and future perspectives. *International Journal of Production Research*, *59*(6), 1875-1900.

Makker, M., Ramanathan, R., & Dinesh, S. B. (2019, December). Post disaster management using satellite imagery and social media data. In *2019 4th International Conference on Computational Systems and Information Technology for Sustainable Solution (CSITSS)* (pp. 1-6). IEEE.

Maksimovic, J., & Evtimov, J. (2023). Positivism and post-positivism as the basis of quantitative research in pedagogy. *Research in Pedagogy*, *13*(1), 208-218.

Malhotra, N. K., Nunan, D., & Birks, D. F. (2017). *Marketing research: An applied approach* (5th ed.). Pearson Education.

Malhouni, Y., & Mabrouki, C. (2022). *Humanitarian and Traditional Supply Chains: An in-depth comparison for better cross-learning.* https://doi.org/10.1109/LOGISTIQUA55056.2022.9938090

Manyika, J. (2022). Getting AI right: Introductory notes on AI & society. *Daedalus*, *151*(2), 5-27. https://doi.org/10.1162/daed_e_01897

Marić, J., Galera-Zarco, C., & Opazo-Basáez, M. (2022). The emergent role of digital technologies in the context of humanitarian supply chains: a systematic literature review. *Annals of Operations Research*, *319*(1), 1003-1044.

Marić, J., Galera-Zarco, C., & Opazo-Basáez, M. (2022). The emergent role of digital technologies in the context of humanitarian supply chains: a systematic literature review. *Annals of Operations Research,* *319*(1), 1003–1044. https://doi.org/10.1007/s10479-021-04079-z

Mathrani, S., & Lai, X. (2021). Big data analytic framework for organizational leverage. *Applied Sciences*, *11*(5), 2340.

Matyi, H., & Tamás, P. (2021). Application of Digital Twin technology in the development of logistics process. *Advanced Logistic Systems-Theory and Practice*, *15*(1), 12-19.

McCoy, J., & Brandeau, M. (2011). Efficient stockpiling and shipping policies for humanitarian relief: UNHCR's inventory challenge. OR Spectrum, 33, 673–698. https://doi.org/10.1007/s00291-011-0237-4

McLachlin, R., & Larson, P. D. (2011). Building humanitarian supply chain relationships: lessons from leading practitioners. *Journal of Humanitarian Logistics and Supply Chain Management, 1*(1), 32–49. https://doi.org/10.1108/20426741111122402

Mehmetoglu, M. (2015). CONDISC: Stata module to perform convergent and discriminant validity assessment in CFA. *Statistical Software Components*.

Minguito, G., & Banluta, J. (2023). Risk management in humanitarian supply chain based on FMEA and grey relational analysis. *Socio-Economic Planning Sciences, 87*, 101551. https://doi.org/10.1016/j.seps.2023.101551

Modgil, S., Singh, R. K., & Hannibal, C. (2022). Artificial intelligence for supply chain resilience: learning from Covid-19. *The International Journal of Logistics Management*, *33*(4), 1246-1268.

Moeiny, E., & Mokhlesi, J. (2011). *Management of Relief Supply Chain & Humanitarian Aids Logistics through Supply Chain Resilience.* University of Borås. http://www.diva-portal.org/smash/get/diva2:1308842/FULLTEXT01.pdf

Moktadir, M. A., Ali, S. M., Paul, S. K., & Shukla, N. (2019). Barriers to big data analytics in manufacturing supply chains: A case study from Bangladesh. *Computers & Industrial Engineering*, *128*, 1063-1075.

Moreira, J., Ferreira Pires, L., van Sinderen, M., Wieringa, R., Singh, P., Costa, P. D., & Llop, M. (2019). Improving the semantic interoperability of IoT Early Warning Systems: the Port of Valencia use case. In *Enterprise Interoperability VIII: Smart Services and Business Impact of Enterprise Interoperability* (pp. 17-29). Springer International Publishing.

Morton, M., & Levy, J. L. (2011). Challenges in disaster data collection during recent disasters. *Prehospital and disaster medicine*, *26*(3), 196-201.

Mubaraka, C. M., Kalulu, R. A., & Salisu, M. J. (2013). Information Technology And Humanitarian Emergency Response Management In WFP Uganda: A Behavioral Perspective. *Global Journal of Commerce and Management Perspective, 2*(3), 147–153.

Munyaka, J. C. B., & Yadavalli, V. S. S. (2021). Using transportation problem in humanitarian supply chain to prepositioned facility locations: a case study in the Democratic Republic of the Congo. *International Journal of System Assurance Engineering and Management*, *12*, 199-216.

Nagurney, A., & Qiang, Q. (2019). Quantifying supply chain network synergy for humanitarian organizations. *IBM Journal of Research and Development*, *64*(1/2), 12-1.

Nanni, S., & Mazzini, G. (2018). Sensornet Early-warning System Integration. In *SENSORNETS* (pp. 77-84).

Nayak, R., & Choudhary, S. (2022). Operational excellence in humanitarian logistics and supply chain management through leagile framework: a case study from a non-mature economy. *Production Planning & Control*, *33*(6-7), 606-621.

Neuman, W. L. (2014). *Social research methods: Qualitative and quantitative approaches* (7th ed.). Pearson Education.

Nikbakhsh, E., & Zanjirani Farahani, R. (2011). 15 - Humanitarian Logistics Planning in Disaster Relief Operations. In R. Z. Farahani, S. Rezapour, & L. B. T.-L. O. and M. Kardar (Eds.), Humanitarian Logisticsn (pp. 291–332). Elsevier. https://doi.org/https://doi.org/10.1016/B978-0-12-385202-1.00015-3

Norwegian Refugee Council. (2016). *Humanitarian principles in practice* (Issue July, pp. 1–3).

Nozari, H., Szmelter-Jarosz, A., & Ghahremani-Nahr, J. (2022). Analysis of the challenges of artificial intelligence of things (AIoT) for the smart supply chain (case study: FMCG industries). *Sensors*, *22*(8), 2931. https://doi.org/10.3390/s22082931

Nurmala, N., de Leeuw, S., & Dullaert, W. (2017). Humanitarian–business partnerships in managing humanitarian logistics. *Supply Chain Management: An International Journal*, *22*(1), 82-94.

Nzekwe-Excel, C. (2021). A qualitative study on the experiences and challenges of MBA students' engagement with a business research methods module. *Journal of Work-Applied Management*, *14*(1), 46-62.

Obilor, E.I. & Isaac, E. (2023). *Convenience and Purposive Sampling Techniques: Are they the Same? 11 (1), 1–7.*

Okoli, C. (2023). Inductive, abductive and deductive theorizing. *Organization Studies*, 44(7), 1071-1089.

Oloruntoba, R., & Gray, R. (2006). Humanitarian aid: an agile supply chain?. *Supply Chain Management: an international journal*, *11*(2), 115-120.

Ortuño, M.T., Ferrer, J.M., Flores, I., & Tirado, G. (2021). Optimization of Humanitarian Logistics. *International Encyclopedia of Transportation*.

Panahi, M., Jaafari, A., Shirzadi, A., Shahabi, H., Rahmati, O., Omidvar, E., ... & Bui, D. T. (2021). Deep learning neural networks for spatially explicit prediction of flash flood probability. *Geoscience Frontiers*, *12*(3), 101076.

Papadopoulos, T., Gunasekaran, A., Dubey, R., Altay, N., Childe, S. J., & Fosso-Wamba, S. (2017). The role of Big Data in explaining disaster resilience in supply chains for sustainability. *Journal of cleaner production, 142*, 1108-1118. https://doi.org/10.1016/j.jclepro.2016.03.059

Parasuraman, A., & Colby, C. L. (2015). An updated and streamlined technology readiness index: TRI 2.0. *Journal of service research*, *18*(1), 59-74.

Park, Y. S., Konge, L., & Artino Jr, A. R. (2020). The positivism paradigm of research. *Academic Medicine*, 95(5), 690-694.

Pathinarupothi, R. K., Durga, P., & Rangan, E. S. (2018). IoT-based smart edge for global health: Remote monitoring with severity detection and alerts transmission. *IEEE Internet of things Journal*, *6*(2), 2449-2462.

Patil, A., Shardeo, V., Dwivedi, A., Madaan, J., & Varma, N. (2021). Barriers to sustainability in humanitarian medical supply chains. *Sustainable Production and Consumption*, *27*, 1794-1807.

Pepe, M., Hesami, M., Small, F., & Jones, A. M. P. (2021). Comparative analysis of machine learning and evolutionary optimization algorithms for precision micropropagation of Cannabis sativa: Prediction and validation of in vitro shoot growth and development based on the optimization of light and carbohydrate sources. *Frontiers in Plant Science*, *12*, 757869. https://doi.org/10.3389/fpls.2021.757869

Pereira, C. R., Christopher, M., & Lago Da Silva, A. (2014). Achieving supply chain resilience: the role of procurement. *Supply Chain Management, 19*(January), 626–642. https://doi.org/10.1108/SCM-09-2013-0346

Petrova, E., Dewing, J., & Camilleri, M. (2016). Confidentiality in participatory research: Challenges from one study. *Nursing ethics*, *23*(4), 442–454.

Petrudi, S. H. H., Tavana, M., & Abdi, M. (2020). A comprehensive framework for analyzing challenges in humanitarian supply chain management: A case study of the Iranian Red Crescent Society. *International Journal of disaster risk reduction*, *42*, 101340.

Pettit, T. J., Fiksel, J., & Croxton, K. L. (2010). Ensuring supply chain resilience: development of a conceptual framework. *Journal of business logistics*, *31*(1), 1-21. https://doi.org/10.1002/j.2158-1592.2010.tb00125.x

Phengsuwan, J., Thekkummal, N. B., Shah, T., James, P., Thakker, D., Sun, R., ... & Ranjan, R. (2019, July). Context-based knowledge discovery and querying for social media data. In *2019 IEEE 20th International Conference on Information Reuse and Integration for Data Science (IRI)* (pp. 307-314). IEEE.

Pizzi, M., Romanoff, M., & Engelhardt, T. (2020). AI for humanitarian action : Human rights and ethics. *International Review of the Red Cross, 102*, 145–180. https://doi.org/10.1017/S1816383121000011

Ponomarov, S. Y., & Holcomb, M. C. (2009). Understanding the concept of supply chain resilience. *The international journal of logistics management*, *20*(1), 124-143.https://doi.org/10.1108/09574090910954873

Prasad, S., Zakaria, R., & Altay, N. (2018). Big data in humanitarian supply chain networks: A resource dependence perspective. *Annals of Operations Research*, *270*(1), 383-413.

Prasanna, S., & Haavisto, I. (2018). Collaboration in humanitarian supply chains: an organisational culture framework. *International Journal of Production Research, 56*, 1–15. https://doi.org/10.1080/00207543.2018.1475762

Preil, D., & Krapp, M. (2022). Artificial intelligence-based inventory management: a Monte Carlo tree search approach. *Annals of Operations Research*, *308*(1), 415-439.

Pringle, J., & Hunt, M. (2015). *Humanitarian Action. In H. ten Have (Ed.), Encyclopedia of Global Bioethics.* Springer. https://doi.org/10.1007/978-3-319-05544-2_235-1

Prodromou, E. H., & Symeonides, N. (2016). Orthodox Christianity and Humanitarianism: An Introduction to Thought and Practice, Past and Present. *The Review of Faith & International Affairs, 14*(1), 1–8. https://doi.org/10.1080/15570274.2016.1145479

Qiao, W., Nan, L., & Kang, T. (2010, August). A study of the influence of public-private partnership on rescue efficiency in humanitarian supply chain. In *2010 IEEE International Conference on Emergency Management and Management Sciences* (pp. 114-117). IEEE. https://doi.org/10.1109/ICEMMS.2010.5563489

Quarshie, A. M., Salmi, A., & Leuschner, R. (2016). Sustainability and corporate social responsibility in supply chains: The state of research in supply chain management and business ethics journals. *Journal of Purchasing and Supply Management*, *22*(2), 82-97.

Ragini, J. R., Anand, P. R., & Bhaskar, V. (2018). Big data analytics for disaster response and recovery through sentiment analysis. *International Journal of Information Management*, *42*, 13-24.

Raman, R., Dhivya, K., Sapra, P., Gurpur, S., Maniraj, S. P., & Murugan, S. (2023, December). IoT-driven Smart Packaging for Pharmaceuticals: Ensuring Product Integrity and Patient Safety. In *2023 International Conference on Artificial Intelligence for Innovations in Healthcare Industries (ICAIIHI)* (Vol. 1, pp. 1-6). IEEE.

Raut, R. D., Yadav, V. S., Cheikhrouhou, N., Narwane, V. S., & Narkhede, B. E. (2021). Big data analytics: Implementation challenges in Indian manufacturing supply chains. *Computers in Industry*, *125*, 103368.

Rege, A. (2023). The Impact of Artificial Intelligence on the Supply Chain in the Era of Data Analytics. *International Journal of Computer Trends and Technology, 71*, 28–39. https://doi.org/10.14445/22312803/IJCTT-V71I1P105

Regis-Hernández, F., & Mora, J. (2015). *Transportation and Distribution in Humanitarian Logistics: A literature review.*

Robson, C., & McCartan, K. (2016). *Real world research* (4th ed.). John Wiley & Sons.

Rodríguez-Espíndola, O., Chowdhury, S., Beltagui, A., & Albores, P. (2020). The potential of emergent disruptive technologies for humanitarian supply chains: the integration of blockchain, Artificial Intelligence and 3D printing. *International Journal of Production Research, 58*(15), 4610-4630. https://doi.org/10.1080/00207543.2020.1761565

Roh, S., & Kim, C.-S. (2016). Comment : Humanitarian Relief Logistics : Prepositioning Warehouse Strategy. *INSIDabcdef_:MS_0001MS_0001 KMI International Journal of Maritime Affairs and Fisheries, 8*(2), 1–17.

Rossetti, P., Garzia, F., Genco, N. S., & Sacchetti, A. (2022). IoT and Edge Computing as Enabling Technologies of Human Factors Monitoring in CBRN

Environment. *International Journal of Cyber Warfare and Terrorism (IJCWT)*, *12*(2), 1-20.

Ruth, N., Crispus, F., & Devis, A. (2024). The Influence Of Media On Humanitarian Intervention. A Case Of South-Sudan Embassy. *Metropolitan Journal of Academic Multidisciplinary Research, 3*, 32–40.

Rysaback-Smith, H. (2015). History and Principles of Humanitarian Action. *Turkish Journal of Emergency Medicine, 15*(Suppl 1), 5–7. https://doi.org/10.5505/1304.7361.2015.52207

Safeer, M., Anbuudayasankar, S. P., Balkumar, K., & Ganesh, K. (2014). Analysing Transportation and Distribution in Emergency Humanitarian Logistics. *Procedia Engineering, 97*, 2248–2258. https://doi.org/https://doi.org/10.1016/j.proeng.2014.12.469

Sahebi, I. G., & Jafarnejad, A. (2018, February). Demand forecasting of emergency resource in humanitarian supply chain. In *Proceedings of the 103rd IRES International Conference, Zurich, Switzerland* (pp. 129-136).

Saïah, F., Vega, D., & Kovács, G. (2023). Toward a common humanitarian supply chain process model: the Frontline Humanitarian Logistics Initiative. *International Journal of Operations & Production Management*, *43*(13), 238-269. https://doi.org/10.1108/IJOPM-01-2023-0054

Salah, K., Alfalasi, A., Alfalasi, M., Alharmoudi, M., Alzaabi, M., Alzyeodi, A., & Ahmad, R. W. (2020, January). IoT-enabled shipping container with environmental monitoring and location tracking. In *2020 IEEE 17th annual consumer communications & networking conference (CCNC)* (pp. 1-6). IEEE.

Samuels, P. (2017). Advice on reliability analysis with small samples-revised version.

Santarelli, G., Abidi, H., Klumpp, M., & Regattieri, A. (2015). Humanitarian supply chains and performance measurement schemes in practice. *International Journal of Productivity and Performance Management, 64*, 784–810. https://doi.org/10.1108/IJPPM-11-2013-0185

Sarker, S., Chatterjee, S., Xiao, X., & Elbanna, A. (2019). The sociotechnical axis of cohesion for the IS discipline: Its historical legacy and its continued relevance. *MIS quarterly*, *43*(3), 695-720.

Saunders, M., Lewis, P., & Thornhill, A. (2019). *Research methods for business students* (8th ed.). Pearson Education.

Schiffling, S., Hannibal, C., Tickle, M., & Fan, Y. (2022). The implications of complexity for humanitarian logistics: A complex adaptive systems perspective. *Annals of Operations Research*, *319*(1), 1379-1410.

Scholten, K., Sharkey Scott, P., & Fynes, B. (2014). Mitigation processes–antecedents for building supply chain resilience. *Supply Chain Management: An International Journal*, *19*(2), 211-228.

Scott, M., Bunce, M., & Wright, K. (2022). The Influence of News Coverage on Humanitarian Aid: The Bureaucrats' Perspective. *Journalism Studies, 23*(2), 167–186. https://doi.org/10.1080/1461670X.2021.2013129

Segalini, A., Savi, R., Cavalca, E., Valletta, A., & Carri, A. (2021). Innovative application of IoT technologies to improve geotechnical monitoring tools and early warning performances. In *Critical Thinking in the Sustainable Rehabilitation and Risk Management of the Built Environment: CRIT-RE-BUILT. Proceedings of the*

International Conference, Iași, Romania, November 7-9, 2019 (pp. 142-146). Springer International Publishing.

Seifert, L., Kunz, N., & Gold, S. (2017). Humanitarian Supply Chain Management Responding to Refugees: A Literature Review. *Journal of Humanitarian Logistics and Supply Chain Management, 8*(3), 398–426. https://doi.org/10.1108/JHLSCM-07-2017-0029

Sekaran, U., & Bougie, R. (2016). *Research methods for business: A skill building approach* (7th ed.). John Wiley & Sons.

Serrato-Garcia, M. A., Mora-Vargas, J., & Murillo, R. T. (2016). Multi objective optimization for humanitarian logistics operations through the use of mobile technologies. *Journal of Humanitarian Logistics and Supply Chain Management*, *6*(3), 399-418.

Shafiq, M., & Soratana, K. (2019). Humanitarian Logistics and Supply Chain Management- A Qualitative Study. *LogForum, 15*(1), 19–38.

Shah, V., Gupta, V., Gandhi, T., & Gupta, R. K. (2023, December). Efficient Medical Supply Chain Forecasting Using Time Series Analysis. In *2023 IEEE International Conference on Computer Vision and Machine Intelligence (CVMI)* (pp. 1-6). IEEE.

Sharma, P., & Joshi, A. (2020). Challenges of using big data for humanitarian relief: lessons from the literature. *Journal of Humanitarian Logistics and Supply Chain Management*, *10*(4), 423-446. https://doi.org/10.1108/JHLSCM-05-2018-0031

Shoyama, K., Cui, Q., Hanashima, M., Sano, H., & Usuda, Y. (2021). Emergency flood detection using multiple information sources: Integrated analysis of natural hazard monitoring and social media data. *Science of the total environment*, *767*, 144371.

Shoyama, K., Cui, Q., Hanashima, M., Sano, H., & Usuda, Y. (2021). Emergency flood detection using multiple information sources: Integrated analysis of natural hazard monitoring and social media data. *Science of the total environment*, *767*, 144371.

Shrivastav, M. (2021). Barriers related to AI implementation in supply chain management. *Journal of Global Information Management (JGIM), 30*(8), 1-19. https://doi.org/10.4018/jgim.296725

Shrivastav, M. (2021). Barriers related to AI implementation in supply chain management. *Journal of Global Information Management (JGIM)*, *30*(8), 1-19.

Siddique, M., Ahmed, T., & Husain, M. S. (2023). Flood monitoring and early warning systems–an iot based perspective. *EAI Endorsed Transactions on Internet of Things*, *9*(2).

Singh, B., & Singh, A. (2015). Strategies for analysing quantitative data in research. *International Journal of Engineering Sciences & Management Research*, *2*(8), 1–5.

Singh, D., Sharma, A., Singh, R. K., & Rana, P. S. (2024). Augmenting supply chain resilience through AI and big data. *Business Process Management Journal*.

Singh, R. K., Gupta, A., & Gunasekaran, A. (2018). Analysing the interaction of factors for resilient humanitarian supply chain. *International Journal of Production Research*, *56*(21), 6809-6827.

Sivarajah, U., Kamal, M. M., Irani, Z., & Weerakkody, V. (2017). Critical analysis of Big Data challenges and analytical methods. *Journal of Business Research, 70*, 263–286. https://doi.org/https://doi.org/10.1016/j.jbusres.2016.08.001

Slater, P. (2024). Fundamentals of quantitative research methods in mental health nursing. *Journal of Psychiatric and Mental Health Nursing*, 31(3), 425-435.

Smyth, C., Dennehy, D., & Fosso-Wamba, S. (2021). A Review of AI in the Supply Chain Industry: Preliminary Findings. In *Responsible AI and Analytics for an Ethical and Inclusive Digitized Society: 20th IFIP WG 6.11 Conference on e-Business, e-Services and e-Society, I3E 2021, Galway, Ireland, September 1–3, 2021, Proceedings 20* (pp. 454-466). Springer International Publishing. https://doi.org/10.1007/978-3-030-85447-8_38

Smyth, C., Dennehy, D., Fosso Wamba, S., Scott, M., & Harfouche, A. (2024). Artificial intelligence and prescriptive analytics for supply chain resilience: a systematic literature review and research agenda. *International Journal of Production Research*, 1–25. https://doi.org/10.1080/00207543.2024.2341415

Sofi-Karim, M., Bali, A. O., & Rached, K. (2023). Online education via media platforms and applications as an innovative teaching method. *Education and Information Technologies*, *28*(1), 507–523.

Sokat, K., Zhou, R., Dolinskaya, I., Smilowitz, K., & Chan, J. (2016). SPECIAL ISSUE | Capturing Real-Time Data in Disaster Response Logistics. *Journal of Operations and Supply Chain Management, 9,* 23. https://doi.org/10.12660/joscmv9n1p23-54

Spence, P. R., & Lachlan, K. A. (2010). Disasters, crises, and unique populations: Suggestions for survey research. *New Directions for Evaluation*, *2010*(126), 95-106.

Stauffer, J. M., & Kumar, S. (2021). Impact of incorporating returns into pre-disaster deployments for rapid-onset predictable disasters. *Production and Operations Management*, *30*(2), 451-474.

Stewart, M., & Ivanov, D. (2022). Design redundancy in agile and resilient humanitarian supply chains. *Annals of Operations Research*, *319*(1), 633-659.

Streefkerk, R. (2023). Inductive vs. deductive research approach | Steps & examples. *Scribbr*. https://www.scribbr.com/methodology/inductive-deductive-reasoning/

Stumpf, J., Besiou, M., & Wakolbinger, T. (2023). Supply chain preparedness: how operational settings, product and disaster characteristics affect humanitarian responses. *Production and Operations Management*, *32*(8), 2491-2509.

Swaminathan, J. M. (2018). Big data analytics for rapid, impactful, sustained, and efficient (RISE) humanitarian operations. *Production and Operations Management*, *27*(9), 1696-1700.

Taleghani, M., & Gheibdoust, H. (2024). *The role of humanitarian supply chain management in environmental crises.*

Tatham, P. H., Spens, K. M., & Taylor, D. (2009). Development of the academic contribution to humanitarian logistics and supply chain management. *Management Research News*, *32*(11).

Teece, D. J., Pisano, G., & Shuen, A. (1997). Dynamic capabilities and strategic management. *Strategic management journal*, *18*(7), 509-533. https://doi.org/10.1002/(SICI)1097-0266(199708)18:7<509::AID-SMJ882>3.0.CO;2-Z

Thayyib, P. V, Mamilla, R., Khan, M., Fatima, H., Asim, M., & Anwar, I. (2023). State-of-the-Art of Artificial Intelligence and Big Data Analytics Reviews in Five Different Domains : A Bibliometric Summary. *Sustainability, 15*(4026).

Tomas, R., Pourghasemi, H. R., & Zhu, A. X. (2022). Flood susceptibility mapping using machine learning: A review. *Journal of Hydrology*, 618, 129123.

Torabi, S. A., Shokr, I., Tofighi, S., & Heydari, J. (2018). Integrated relief pre-positioning and procurement planning in humanitarian supply chains. *Transportation Research Part E: Logistics and Transportation Review*, *113*, 123-146.

Trist, E. L., & Bamforth, K. W. (1951). Some social and psychological consequences of the longwall method of coal-getting: An examination of the psychological situation and defences of a work group in relation to the social structure and technological content of the work system. *Human relations*, *4*(1), 3-38.

Tukamuhabwa, B. R., Stevenson, M., Busby, J., & Zorzini, M. (2015). Supply chain resilience: Definition, review and theoretical foundations for further study. *International Journal of Production Research,* *53*(18), 5592–5623. https://doi.org/10.1080/00207543.2015.1037934

United Nations. (2022). Record numbers of people need humanitarian assistance. *Humanitarian Affairs.* https://unis.unvienna.org/unis/en/topics/related/2023/humanitarian-need.html

Velev, D., & Zlateva, P. (2023). Challenges of artificial intelligence application for disaster risk Management. *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, *48*, 387-394. https://doi.org/10.5194/isprs-archives-XLVIII-M-1-2023-387-2023

Venkatesh, V. G., Zhang, A., Deakins, E., Luthra, S., & Mangla, S. (2019). A fuzzy AHP-TOPSIS approach to supply partner selection in continuous aid humanitarian supply chains. *Annals of Operations Research*, *283*, 1517-1550.

Wade, M., & Hulland, J. (2004). The resource-based view and information systems research: Review, extension, and suggestions for future research. *MIS quarterly*, 107-142. https://doi.org/10.2307/25148626

Wagner, S., & Thakur-Weigold, B. (2018). Supporting collaboration in humanitarian supply chains – insights from a design science project. *Production Planning & Control, 29*, 1130–1144. https://doi.org/10.1080/09537287.2018.1542175

Walker, B., Holling, C. S., Carpenter, S. R., & Kinzig, A. (2004). Resilience, adaptability and transformability in social–ecological systems. *Ecology and society*, *9*(2). http://www.ecologyandsociety.org/vol9/iss2/art5/

Wamba, S. F., Gunasekaran, A., Akter, S., Ren, S. J. F., Dubey, R., & Childe, S. J. (2017). Big data analytics and firm performance: Effects of dynamic capabilities. *Journal of business research*, *70*, 356-365. https://doi.org/10.1016/j.jbusres.2016.08.009

Warnier, M., Alkema, V., Comes, T., & Van de Walle, B. (2020). Humanitarian access, interrupted: dynamic near real-time network analytics and mapping for reaching communities in disaster-affected countries. *Or Spectrum*, *42*, 815-834.

Wernerfelt, B. (1984). A resource-based view of the firm. *Strategic management journal*, *5*(2), 171-180. https://doi.org/10.1002/smj.4250050207

Whetsell, T. A., & Shields, P. M. (2021). The potential of working hypotheses for deductive exploratory research. *Quality & Quantity*, 55(3), 993-1010.

Wieland, A., & Wallenburg, C. M. (2013). The influence of relational competencies on supply chain resilience: a relational view. *International journal of physical distribution & logistics management*, *43*(4), 300-320.

Wooldridge, J. M. (2013). Introductory Econometrics 5th ed.

Woolley, K., Kupor, D., & Liu, P. J. (2023). Does company size shape product quality inferences? Larger companies make better high-tech products, but smaller companies make better low-tech products. *Journal of Marketing Research*, *60*(3), 425-448.

World Economic Forum. (2025). *Leveraging AI collaboration to strengthen supply chains for humanitarian aid*. World Economic Forum.

Xu, W., Li, W., Proverbs, D., & Chen, W. (2023). An Evaluation of the Humanitarian Supply Chains in the Event of Flash Flooding. In *Water* (Vol. 15, Issue 18). https://doi.org/10.3390/w15183323

Yadav, D. K., & Barve, A. (2015). Analysis of critical success factors of humanitarian supply chain: An application of Interpretive Structural Modeling. *International Journal of Disaster Risk Reduction, 12*, 213–225. https://doi.org/https://doi.org/10.1016/j.ijdrr.2015.01.008

Yagci Sokat, K., Zhou, R., Dolinskaya, I. S., Smilowitz, K., & Chan, J. (2016). Capturing real-time data in disaster response logistics. *Journal of Operations and Supply Chain Management (JOSCM)*, *9*(1), 23-54.

Yakobi, K., Scholtz, B., & Vom Berg, B. (2020, April). A conceptual model of the challenges of social media big data for citizen e-participation: a systematic review. In *Conference on e-Business, e-Services and e-Society* (pp. 247-259). Cham: Springer International Publishing. https://doi.org/10.1007/978-3-030-45002-1_21

Yang, H., Yang, L., & Yang, S. H. (2011). Hybrid Zigbee RFID sensor network for humanitarian logistics centre management. *Journal of Network and Computer Applications*, *34*(3), 938-948.

Yousefzadeh, R. (2020). A Probabilistic Framework for Optimizing Real-time Decisions in Humanitarian Aid Delivery Systems. *arXiv preprint arXiv:2006.11953*.

Zabinsky, Z. B., Zameer, M., Petroianu, L. P., Muteia, M. M., & Coelho, A. L. (2021). Route Optimization Tool (RoOT) for distribution of vaccines and health products. *Gates open research*, *5*. https://doi.org/10.12688/gatesopenres.13219.2

Zain, M.R., Mohd Zahari, H., & Mohd Zainol, N. A. (2023). Inter-agency information sharing coordination on humanitarian logistics support for urban disaster management in Kuala Lumpur. *Frontiers in Sustainable Cities*, *5*, 1149454.

Zamani, E. D., Smyth, C., Gupta, S., & Dennehy, D. (2023). Artificial intelligence and big data analytics for supply chain resilience: a systematic literature review. *Annals of Operations Research, 327*(2), 605–632. https://doi.org/10.1007/s10479-022-04983-y

Zambrano, A. M., Perez, I., Palau, C., & Esteve, M. (2017). Technologies of internet of things applied to an earthquake early warning system. *Future Generation Computer Systems*, *75*, 206-215.

Zhang, H., Strawderman, L., & Eksioglu, B. (2011). The Role of Intermodal Transportation in Humanitarian Supply Chains. *Journal of Emergency Management, 9*, 25–36. https://doi.org/10.5055/jem.2011.0044

Zhang, J., Wang, Z., & Ren, F. (2019). Optimization of humanitarian relief supply chain reliability: A case study of the Ya'an earthquake. *Annals of Operations Research*, *283*(1), 1551-1572.

Zhang, X., & Zhang, M. (2023). Generalized Neural Networks for Real-Time Earthquake Early Warning. *arXiv preprint arXiv:2312.15218.*

Zhou, C., Ma, J., Douge, L., Chew, E. P., & Lee, L. H. (2023). Reinforcement Learning-based approach for dynamic vehicle routing problem with stochastic demand. *Computers & Industrial Engineering*, *182*, 109443.

Zikmund, W. G., Babin, B. J., Carr, J. C., & Griffin, M. (2018). *Business research methods* (9th ed.). Cengage Learning.

Zouari, D., Ruel, S., & Viale, L. (2021). Does digitalising the supply chain contribute to its resilience?. *International Journal of Physical Distribution & Logistics Management*, *51*(2), 149-180.

Zuhr, P., Rissmann, L., & Meißner, S. (2022). Framework for planning and implementation of Digital Process Twins in the field of internal logistics. *IFAC-PapersOnLine*, *55*(10), 2221-2227.

Zyoud, M. M., Bsharat, T. R. K., & Dweikat, K. A. (2024). Quantitative research methods: Maximizing benefits, addressing limitations, and advancing methodological frontiers. *ISRG Journal of Multidisciplinary Studies*, *2*(4), 11-14.

APPENDIX A: Survey Questionnaire

Dear Respondent,

My name is Emmanuel Ahatsi and I am studying for a Doctor of Engineering (D.Eng.) degree in Industrial Engineering with the Durban University of Technology. This questionnaire seeks to assess how digital technologies may combine to increase humanitarian supply chain resilience, aimed at optimizing robustness and effectiveness of the supply chain network in Humanitarian organizations.

You are hereby invited to complete this questionnaire. The questionnaire would help us Improve humanitarian supply chains in our resolve to transition supply chain network from reactive to anticipatory leading to enhanced disaster preparedness, optimized resource allocation and timely aid distribution.

All the information gathered in this research is for academic purposes **ONLY** and will be treated with utmost confidence.

I would like to thank you in advance for your time and effort in completing this questionnaire. Should you require additional information concerning this study or further clarity, you may contact the researcher as per the following details: e-mail 22384754@dut4life.ac.za or Mobile number +233243779343

Thank you

Yours Faithfully

Emmanuel Ahatsi

Please tick [✓] the most appropriate response in the boxes provided below

Section 1: Demographic Information

1. What is your age?

Under 25 [ ] 25-34 [ ] 35-44 [ ] 45-54 [ ] 55 and above [ ]

2. What is your gender?

Male [ ] Female [ ]

3. What is your highest level of education?

Secondary School [ ] Bachelor's Degree [ ] Masters Degree [ ] Doctorate [ ]

Professional Certification [ ] Other (Please specify): _____________

4. What is your Current Professional Role

Supply Chain Manager [ ] Data Scientist [ ] IT Specialist [ ] Operations Leader [ ]

Other (Please specify): _____________

5. Years of Experience in Humanitarian Supply Chain

Less than 3 years [ ] 3-5 years [ ] 6-10 years [ ] More than 10 years [ ]

Section 2: Organizational Information

6. Country of Operation

Ghana [ ] South Africa [ ] Both countries [ ]

7. Type of Humanitarian Organization

International NGO [ ] Local NGO [ ] Government Agency [ ]

United Nations Agency [ ] Other (Please specify): _____________

8. Primary Area of Supply Chain Operations

Disaster Response [ ] Medical Supply Chain [ ] Food Distribution [ ] Logistics and Transportation [ ] Warehouse Management [ ] Other (Please specify): _____________

9. Years of Organization's Experience with AI-BDA

Less than 1 year [ ] 1-3 years [ ] 4-5 years [ ] More than 5 years [ ]

Section 3: AI-BDA techniques in humanitarian supply chains

Please rate the extent to which your organization uses the following AI-BDA techniques in humanitarian supply chains on a scale of 1 to 5, where 1 = Not at all, 2 = To a small extent, 3 = To a moderate extent, 4 = To a large extent, 5 = To a very large extent.

SN		1	2	3	4	5
	Time-Series Forecasting					
1	Our organisation uses AI for demand prediction in humanitarian operations					
2	We employ machine-learning algorithms for supply chain disruption forecasting.					
3	Our organisation utilises predictive analytics for medical inventory management.					
	Early Warning Systems					
1	Our organisation employs machine learning for disaster risk prediction					
2	We use AI-powered systems for flood susceptibility prediction.					
3	Our early warning systems help pre-position supplies before disasters.					
	Logistics Optimization					
1	Our organisation uses AI algorithms to optimise delivery routes during crises.					
2	We employ multi-objective optimisation models for resource allocation.					

3	Our organisation uses AI for transportation network optimisation.					
	Real-time Monitoring					
1	Our organisation employs real-time tracking systems for supply visibility					
2	We use AI to monitor resource distribution in real-time.					
3	Our organisation utilises technology for real-time location tracking of humanitarian supplies.					

Section 4: AI and Big Data (AI-BDA) applications in improving the resilience of humanitarian supply chains

Please rate the extent to which you agree to the extent of AI and Big Data (AI-BDA) applications in improving the resilience of humanitarian supply chains on a scale of 1 to 5, where 1 = Strongly Disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, 5 = Strongly Agree.

SN		**1**	**2**	**3**	**4**	**5**
1	We quickly restore the flow of items with the help of AI-driven technologies.					
2	Information gathered using AI-driven technology help us provide necessary relief materials during unexpected disruptions.					

3	We maintain a buffer stock of important relief items to tackle demand and supply uncertainties.					
4	We quickly repair the damages caused to the basic property, schools, and other essential centres.					

Section 5: Challenges and barriers in adopting and implementing AI and Big Data Analytics (AI-BDA) within humanitarian supply chains.

Please rate the extent to which you agree to the barriers in adopting and implementing AI and Big Data Analytics (AI-BDA) within humanitarian supply chains on a scale of 1 to 5, where 1 = Strongly Disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, 5 = Strongly Agree.

SN		**1**	**2**	**3**	**4**	**5**
	Technical Barriers (TB)					
1	Our organisation faces infrastructure limitations in implementing AI-BDA					
2	Data integration complexity poses a significant challenge.					
3	Limited data accessibility hinders our AI-BDA implementation.					
	Organisational barriers					
1	Lack of top management support affects our AI-BDA implementation					

2	Our organisation faces resistance to change in adopting AI-BDA.					
3	Cultural barriers affect our AI-BDA implementation.					
	Resource barriers					
1	Financial constraints limit our AI-BDA implementation					
2	Skill gaps among staff affect our adoption of AI-BDA.					
3	Lack of technical expertise hinders our AI-BDA implementation.					

Thank you for your response