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The Impact of Artificial Intelligence in Enhancing Operational Performance of Logistics and Freight Forwarding Companies in Pakistan

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Abstract

The rapid advancement of Artificial Intelligence is transforming logistics and freight forwarding globally by providing better insights to make better decisions to improve operational efficiency of overall supply chain processes. However still in Pakistan, the efficient usage of Artificial Intelligence in logistics sector is limited due to infrastructure gaps, limited funds and regulatory challenges. My topic will look in to the purpose of Artificial Intelligence in enhancing the operational performance of logistics and freight forwarding industry in Pakistan. It examines how AI competencies such as data analytics, live data processing, optimization and automation will help to address operational inefficiencies, improve process consistency, and strengthen overall performance. The research also explores the challenges hindering AI integration and highlights the significance of consistent supply chain processes in maximizing AI's impact. By concentrating on these crucial areas, this study goal is to clarify some important insights which logistics companies can apply to enhance decision-making, competitiveness and quality in a business environment that is changing quickly.

Keywords: Artificial Intelligent, Operational performance, Supply chain consistency

Introduction

1.1. Introduction

The freight-forwarding and logistics industry is significant to Pakistan's economy as it facilitates trade. However, due to globalization and competition, there has been a rise in the need for enhanced efficiency and reliability in functions, while traditional logistics methods have been attributed to high costs of operation and delays in activities (Singhal & Singhal, 2012; Gachui, 2020). On the other hand, Artificial Intelligence has been recognized as a significant enabling force in the area of logistics because of advancements it has created in the realm of decision-making and automation of activities using data-driven technologies (Javaid et al., 2022; Barua et al., 2020). Research has evidenced that AI implementation has increased cost-effectiveness and time sensitivity of activities, but its implementation in the developing economies has not been well-documented from an empirical perspective (Dubey et al., 2020; Malhotra & Kharub, 2025). This paper explores the effect of AI implementation on the efficiency of the activities of logistical and freight-forwarding firms in Pakistan because of its significant research void left in the literature documentation surrounding the theme of research (Channa et al., 2024; Du Plessis et al., 2025).

1.2. Background

The logistics & freight forwarding industry is critical to Pakistan's economy; nonetheless, it continues to face issues such as high cost of doing business, high lead time, & lack of reliability, making it internationally uncompetitive (Singhal & Singhal, 2012; Gachui, 2020). Internationally, Artificial Intelligence has revolutionized the field of logistics & supply chain management by providing means for automation, real-time forecasting, & data-driven decision support, which has led to an increase in operational & reliability efficiency (Pournader et al., 2021; Dubey et al., 2020). Empirical researches have reaffirmed that using AI & machine learning algorithms for predictive analytics improves route planning & usage, forcast accuracy, & resource allocation & utilization in logistic services (Barua et al., 2020; Javaid et al., 2022). Although there have been proven benefits of AI usage, however, its adoption in Pakistan's logistic services has been impeded by infrastructure bottlenecks, & it still lacks specific empirical researches on such issues; consequently, this research study intends to fill this research gap (Channa et al., 2024).

1.3. Problem Statement

In the global context, the increasing adoption of Artificial Intelligence (AI) in the logistics and freight forwarding industry has resulted in improving service quality and increasing competitiveness (Pournader et al., 2021; Javaid et al., 2022). Even though the adoption of AI in developed countries has shown improvements in routing, minimizing delays, and improving overall performance, the Pakistan logistics environment is still struggling with increased costs of operations, cargo handling delays, and variability in service quality (Dubey et al., 2020; Gachui, 2020). The major reason why the adoption of AI in Pakistan is still limited is that of infrastructural, regulatory, and talent investment barriers, thereby increasing dependency on traditional methods that limit infrastructure flexibility and competitiveness (Channa et al., 2024; Du Plessis et al., 2025). In addition, empirical studies on the influence of AI technology on improving specific operations in the Pakistan freight forwarding environment are limited, creating a knowledge gap that needs to be explored to understand the applicability of using AI technology to improve operations in this environment (Pournader et al., 2021; Dubey et al., 2020).

1.4. Research Gap

Although AI was widely recognized to improve logistics and supply chain performance, extant empirical research is mostly concentrated on manufacturing industries, e-commerce logistics, and firms operating in developed economies (Dubey et al., 2020; Pournader et al., 2021; Javaid et al., 2022). Those studies with a focused emphasis on logistics and freight forwarding service providers remain limited, especially in the developing country context where infrastructural constraints, fragmented processes, and limitations related to data are more incumbent (Barua et al., 2020; Modgil et al., 2022). Furthermore, prior studies have mainly considered AI adoption outcomes in terms of reduced costs or enhanced forecasting accuracy, while inadequate consideration was paid to how AI enhances operational efficiency through mechanisms that are logistics-specific, such as coordination, reliability, and consistency of supply chain processes (Hazen et al., 2014; Singhal & Singhal, 2012). Empirical evidence relevant to these relationships is scant in the context of Pakistan's logistics and freight forwarding sector. Consequently, there is a clear gap in the literature on context-specific empirical evidence on how AI adoption influences operational efficiency in Pakistan's logistics and freight forwarding industry, with particular emphasis on the role of supply chain consistency as an explanatory factor.

1.5. Research Objectives

Following are the objectives of the study:

- Impact of AI use on operational efficiency: the mediating role of consistency in supply chain.

1.6. Research Questions

The research questions are as follows:

- What is the effect of the usage of AI on operational efficiency, with a mediating role for supply chain consistency?
- Which challenges come with adopting AI in Pakistan's logistics and freight forwarding sector?
- What future trends and limitations do AI systems have in upgrading logistics and freight forwarding operations in Pakistan?

1.7. Significance of the study

The study is important because it looks at the use of Artificial Intelligence in improving decision-making, operational efficiency, and process visibility within the operation of logistics and freight forwarding. With this view, AI-powered technologies like automation, predictive analytics, and real-time tracking can help improve operational performance while reducing inefficiencies (Ali et al., 2024; Pournader et al., 2021). In Pakistan, where infrastructural constraints, high costs, and inconsistent operations are common features that pose critical challenges to the logistics sector, there is limited empirical evidence on AI adoption (Afolabi et al., n.d.; Channa et al., 2024). This paper highlights how SCC plays a crucial role in the implementation of such improvements, which will lead to more efficient and competitive operations.

1.8. Scope of the Research

The research paper aims to identify the impact of Artificial Intelligence (AI) on improving the functional efficiency of logistics and freight forwarding companies in the Pakistani market. With this background, the research study aims to identify the impact and use of AI-based intelligent systems in improving the efficiency of demand and supply, and, more specifically, improving the areas of key performance challenges (Du Plessis et al., 2025). The research will also identify the impact of the enhancement of SCC, which, by the use of AI-based intelligent systems, will, in turn, positively impact the efficiency of logistics and freight forwarding operations. Since the research aims to identify the impact and use of AI-based systems in the Pakistani market, the findings of the research study may also help develop understanding and insights for developing markets (Du Plessis et al., 2025).

1.9. Organization of the Thesis

The aim of the research work shall be to demonstrate a comprehensive analysis of the effects caused by the positivity surrounding AI on working efficiency under logistics and freight forwarding companies operating within Pakistan. The research will have a logical flow from identifying problems and carrying out literature reviews to finally exploring via research methods. The framework of my thesis will be as below:

Chapter 1 – Introduction - This chapter establishes the groundwork for research as it contains background details, problem statement, research objectives, research questions, and scope. In addition it underscores the importance and relevance of research on finding the role of AI intervention and its benefits on operational performance within the Pakistani Logistics and Freight forwarding Industry.

Chapter 2 – Literature Review - This chapter analyze the literature as regards to the application of AI to logistics and freight logistics and applications to freight operations and logistics services within the freight forwarding sector. AI is identified as an important contributor to improved operations performance via increased process efficiency and optimized demand to supply matching and, therefore, better decision models associated with logistics operations. In addition, potential barriers to the execution of AI-based solutions and potential gaps in the existing literature which are relates to AI implementation in the logistics and transportation sector are highlighted, thereby establishing a rationale for the conduct of further research regarding AI and the use of AI within logistics and freight transportation.

Chapter 3 – Research Methodology - This chapter proposes a research framework, data collection techniques, sampling techniques, and analysis techniques used to examine the impact of AI use on the performance levels of logistics and freight forwarding businesses.

This research methodology constitutes a systematic process to examine the significance of AI integration to the efficiency, dependability, and competitiveness levels within logistics and freight forwarding businesses by relying on survey data and quantitative analysis to examine the link between AI use and performance outcomes.

Chapter 4– Findings- This chapter highlights the empirical findings drawn from data analysis. This chapter features various descriptions, demographic analyses, and evaluations of models of measurement and structure. The hypotheses are tested through various statistical methods, and their findings are discussed in accordance with the research targets and conceptual framework. This chapter gives a very detailed discussion on findings according to AI implementation, supply chain alignment, and operational efficiency.

Chapter 5 – Conclusion- This chapter summarizes the major findings from conducting the research and its implications from the perspectives of theory and practice. It relates the findings from carrying out the research with various literatures available in the field, pointing out the contribution made by the research in the realm of knowledge and practice.

Chapter 6 – Future Recommendations - Future Recommendations - This chapter brings forward recommendations and conclusions that are based on the study's findings and are meant to guide practitioners, policymakers, and researchers. This subject will point out fields that require managerial action and strategic implementation in terms of using AI and supply chain management. Finally, limitations and recommendations for future studies are presented.

LITERATURE REVIEW

2.1. Operational Performance

Operational performance refers to the degree of effectiveness and efficiency with which logistics and freight forwarding firms carry out their core activities, including cargo handling, storage, transportation, and timely delivery, in order to meet customer requirements and achieve organizational objectives (Singhal & Singhal, 2012; Gachui, 2020). It also reflects an organization’s ability to deliver consistent service quality and respond effectively to market demands while operating in a dynamic and competitive logistics environment (Bortolini et al., 2019; Loske & Klumpp, 2021). Operational excellence has remained a critical factor for enhancing service reliability, customer satisfaction, and cost competitiveness in logistics operations, particularly in markets characterized by increasing uncertainty and competitive pressure (Hazen et al., 2014; Dubey et al., 2020). In the context of Pakistan, operational performance has become a central concern for logistics and freight forwarding firms due to rising trade volumes, growing customer expectations, infrastructural limitations, and the increasing need for cost-efficient and time-sensitive transportation solutions (Gachui, 2020; Channa et al., 2024).

2.2. Artificial Intelligence Usage (AIU)

Artificial Intelligence (AI) is increasingly transforming logistics and freight forwarding operations by enabling more efficient, visible, and data-driven decision-making processes (Dubey et al., 2020; Pournader et al., 2021). In this study, AI usage refers to the application of technologies such as machine learning, predictive analytics, intelligent automation, and real-time data processing to optimize logistics activities, including demand forecasting, route planning, cargo handling, and delivery coordination (Belhadi et al., 2021; Barua et al., 2020; Javaid et al., 2022). AI enhances resource allocation and operational responsiveness by improving coordination across logistics networks, thereby reducing delays, operational inefficiencies, and service variability (Modgil et al., 2022; Loske & Klumpp, 2021). These capabilities support faster and more reliable service delivery, which is particularly valuable for logistics and freight forwarding firms operating in developing countries such as Pakistan, where digital transformation remains at an early stage and operational inefficiencies are prevalent (Channa et al., 2024; Malhotra & Kharub, 2025).

2.3. Supply Chain Consistency (SCC)

Logistics and freight forward operations utilize supply chain "consistency" to keep stable, reliable and predictable processes throughout every service delivery stage (Bendoly et al. 2018). This allows goods to flow and receive information without interruption; orders meet the delivery date (therefore, customer expectations); recovery after disruptive events is efficient (therefore, reliability) (Singhal and Singhal 2012). Consistency in supply chain operations is tied to coordination, sharing of information and adherence to agree upon standards of performance for the entire logistics network to operate efficiently (Zhao et al. 2010). Incorporating AI into the logistics supply chain (AI) provides companies the necessary tools to have more consistency across the logistics supply chain because it improves visibility of product movement within the logistics SC, forecasts more accurately, and provides an ability to rapidly respond to disruptions (Modgil et al. 2022). Through predictive analytics, automation and live data processing, AI helps organizations to maximize their material flows, better coordinate their resources and reduce the time of delivery for each shipment of products, therefore creating the foundation for better reliability in the logistics operations of logistics networks and providing the foundation for enhancing the operational performance of those networks particularly in a developing economy such as Pakistan, where logistics supply networks are in a stage of continual development.

2.4. AI Usage Impact on Operational Performance

Logistics operational efficiency represents the effectiveness, ability, and quality of the services provided by the organization (Singhal & Singhal, 2012; Gachui, 2020). AI improves the above aspects by using sophisticated data processing, route optimization, and automation, which result in the reduction of errors and delays (Chen et al., 2015; Bortolini et al., 2019; Dubey et al., 2020). Real-time monitoring and decision-making capabilities of artificial intelligence help logistics companies to react to changes in demand, thus improving the reliability of services (Barua et al., 2020; Govindan, 2024; Loske & Klumpp, 2021).

In addition, AI indirectly helps in the efficiency of business operations by enabling consistency in the supply chain and making it easy to coordinate activities such as procurement, storage, logistics, and billing (Hazen et al., 2014; Leung et al., 2020; Ruiz-Hernández et al., 2019). AI helps companies maintain consistent and reliable operations, which improves responsiveness and competitive advantage, especially in growing economies like Pakistan (Modgil et al., 2022; Malhotra & Kharub, 2025; Zhao et al., 2010). In general, AI helps in faster, more flexible, and more efficient logistics operations and improves the predictability of supply chain activities.

2.5. Theoretical background

This study investigates the role of AI in enhancing the performance of logistics and freight forwarders by using two strategies under the realm of strategic management theories, namely the Resource-Based View Perspective and Dynamic Capabilities Theory. Both theories can explain how AI acts as a valuable resource for logistics enterprises and how it works as a dynamic capability for improving the efficiency, coordination, and agility of the enterprises.

2.5.1. Resource-Based View (RBV)

Barney (1991) Resource-Based View proposes that a sustained competitive advantage and outstanding performance can be ensured by exploiting VRIN resources. When it comes to the logistics and freight forwarding industry, AI-related technologies, including automation software, predictive analytics software, or routing software, may be classified as strategic resources (Belhadi et al., 2021). Through the application of these technologies, logistics companies will benefit from increased operational efficiency resulting from improved real time visibility and analytical decision making. AI improves cross-functional collaboration within the procurement, warehousing and transportation departments, which in turn reduces logistical inefficiencies, hence improving the reliability of deliveries (Dash et al., 2019; Leung et al., 2020). Logistical firms that utilize AI as a valuable organization resource can therefore achieve exceptional performance in terms of service quality, cost-effectiveness and responsiveness, which are important aspects of operational performance. In this way, RBV provides support for the present study by presenting AI as an intangible strategic resource that enables increased efficiency and competitiveness for both organizations and the logistics industry (Barney, 1991; Wernerfelt, 1984).

2.5.2. Dynamic Capabilities Theory

The Dynamic Capabilities Theory was presented by Teece, Pisano, and Shuen (1997) as an extension of the RBV in that it states that instead of just having access to certain valuable resources, the ability to integrate and develop those resources and adjust them as needed based on the demands placed on an organization will sustain an organization's competitive advantage. In the logistics and freight forwarding industries, which are both subject to fluctuations in demand, changing supply chains, and increased competition, the deployment of AI technologies gives organizations the ability to sense, seize, and transform their operational capabilities as they continue to grow (Teece, 2007; Eisenhardt & Martin, 2000).

Additionally, utilizing AI technologies enables organizations to better forecast future market conditions and make operational decisions based on real-time data, as well as provide for increased operational efficiency and responsiveness by collaborating with multiple areas within the organization to coordinate activities (Modgil et al., 2022; Sorooshian et al., 2022). The organizations that use AI technologies are also constant in modifying their procedures in response to evolving conditions and thus adapt quickly and reduce down times to succeed in their operations (Imam, 2024; Shao et al., 2019). Therefore, the application of the DCT to organizations demonstrates that although AI enhances an organization's existing processes, it also provides the organization with the means to continuously evolve, thereby increasing operational performance over time.

2.1. Summary of Literature Review

Table 1 Summary of Literature Review

Construct	Definition	Source
Artificial Intelligence Usage	AI Usage corresponds with the implementation and utilization of intelligent technologies, which include predictive analytics and automation tools as well as decision support systems with the objective of optimizing and improving logistics and minimizing delays. According to empirical research, AI facilitates and enhances optimization relating to routes and warehouses.	Belhadi et al. (2021); Modgil et al. (2022); Shao et al. (2019); Leung et al. (2020)
Network Optimization	Network optimization is improved by the use of artificial intelligence-based technology to drive lower transportation costs and faster delivery times through enhanced monitoring capabilities in the logistics and freight forwarding industries.	Pournader et al. (2021), Leung et al. (2020)
Cost Analytics	The usage of AI-based analytical tools to analyze the costs associated with procurement and logistics processes provides insight that can drive better procurement and operational decision-making and improve the efficiency of logistics operations.	Dash et al. (2019), Shao et al. (2019)
Inventory Management	Through AI, forecasting and error reduction are enhanced in order to improve inventory accuracy and provide timely access to products, thus increasing the operational efficiencies of inventory management within Logistics and Freight Forwarding Industries.	Jauhar et al. (2023), Belhadi et al. (2021)
Integration	AI facilitates seamless integration of supply chain process by coordination with the warehouse, transportation and last-mile logistics functions is achieved, thereby increasing the efficiency of logistics operations.	Dubey et al. (2020)
Supply Chain Consistency	Logistics and freight forwarding operations possess high levels of reliability and consistency through the timely delivery of goods; the uniformity of products' quality and inventory management systems; the ability to coordinate various logistical processes together; and the ability to withstand disruptions in operations.	Hazen et al. (2014), Modgil et al. (2022),
Operational Efficiency	The capability of logistics and freight forwarding operations is shown through	Malhotra & Kharub (2025)

	the provision of timely, accurate and dependable deliveries, the responsiveness to fluctuations in consumer demand and supplier availability; utilization of resources in the best way possible, as well as the lowest possible cost per unit when compared to competitors' operations.	

2.7. Research Hypotheses

Artificial Intelligence (AI) has recently proven to be a key efficiency enabler in the logistics and freight forwarding industry as a result of the digital transformation process. The current literature suggests that the application of AI in areas such as inventory management, network planning, routing, and demand forecasting has led to increased operational efficiency through the reduction of delays and the optimization of resource use (Bányai, 2018; Jang et al., 2023). Other research has suggested that AI-based analytics and automation have improved the reliability of services and processes in logistics, thus leading to improved operational performance (Dash et al., 2019; Loske & Klumpp, 2021). Based on the above, the current study proposes the following research hypotheses:

2.7.1. Operational Efficiency and AI Usage

Artificial Intelligence (AI) is increasingly transforming the operations of the supply chain and freight forwarding industry by improving the efficiency of operations using predictive analytics, automation, and data-driven decision-making. AI applications help with the primary logistics functions of route optimization, tracking, warehousing, and resource management, thus ensuring faster, more accurate, and reliable freight operations (Bányai, 2018; Dash et al., 2019; Pournader et al., 2021). AI applications help with improved demand forecasting, workflow optimization, and end-to-end visibility, which together help in reducing operational errors and costs, while also improving responsiveness and consistency in logistics operations (Dubey et al., 2020; Loske & Klumpp, 2021). Empirical summaries by (Belhadi et al., 2021; Modgil et al. 2022) have provided strong evidence that AI-based logistics systems have helped in improving process efficiency, customer satisfaction, and competitiveness, especially through enhanced supply chain resilience and logistics process coordination. While AI has immense potential for achieving operational excellence, initial studies have revealed organizational doubts about the profitability and return on investment of AI adoption in logistics operations (Kumar et al., 2017). However, more recent empirical evidence suggests that logistics companies, including those in emerging markets such as Pakistan, have begun to experience tangible efficiency gains and performance improvements from AI adoption, thus dispelling initial doubts and emphasizing the importance of AI in logistics operations (Malhotra & Kharub, 2025; Du Plessis et al., 2025).

H1: AI usage positively affects Operational Efficiency.

2.7.2. Supply Chain Consistency and AI Usage

The continuous monitoring of the supply chain, facilitated by AI, provides enhanced visibility and accurate information flow for procurement, warehousing, transportation, billing, and customer communications. As a result, AI assists companies in avoiding disruptions and coordinating all parts of their given supply chain with greater effectiveness and greater visibility, as well as greater detection and correction of irregularities occurring in their day-to-day processes at an early stage, and assisting with standardized decision-making processes throughout their given supply chain (Dash et al., 2019; Zhou et al., 2023). Moreover, companies can benefit from and exploit predictive analytics for increased effectiveness and capability to handle demand and supply fluctuations proactively to ensure day-to-day reliability and consistency with predictive analytics (Belhadi et al., 2021; Modgil et al., 2022).

H2: AI Usage affects Supply Chain Consistency.

2.7.3. Operational Efficiency and Supply Chain Consistency

Supply Chain Consistency refers to the standardized and stable execution of supply chain processes, which helps to minimize process variability and operational disruptions in logistics operations (Singhal & Singhal, 2012). Consistent supply chain processes help to achieve just-in-time delivery, minimize errors, and improve coordination among supply chain partners, thus improving overall operational efficiency (Loske & Klumpp, 2021). If logistics operations like procurement, storage, transportation, and paperwork are carried out in a consistent manner, it results in smoother operations and improvements in speed, accuracy, and reliability of operations (Bortolini et al., 2019; Dubey et al., 2020). Additionally, supply chain consistency helps to share information and minimize uncertainty, thus allowing logistics teams to react to changes in demand and operations (Pournader et al., 2021). Previous research work suggests that increased consistency in supply chain processes helps to improve resource use and operational efficiency (Belhadi et al., 2021; Modgil et al., 2022).

H3: Supply Chain Consistency positively affects Operational Efficiency.

2.7.4. Operational Efficiency, Supply Chain Consistency, AI Usage

SCC helps improve logistics and freight forwarding performance by ensuring consistent delivery, consistent operational processes, synchronized inventory, and consistent execution of supply chain processes (Singhal & Singhal, 2012). Consistent logistics processes help minimize variability and disruptions, making it easier to coordinate logistics functions and supply chain partners, which directly helps improve operational efficiency (Gunasekaran et al., 2017; Loske & Klumpp, 2021). The role of AI further strengthens supply chain consistency by ensuring improved data accuracy, real-time visibility, and proactive decision-making in logistics processes (Wamba et al., 2017). AI-based technologies help with predictive analysis, risk detection, and disruption management, allowing logistics companies to better manage demand variability and operational uncertainty (Bányai, 2018; Jang et al., 2023). Existing empirical research supports that the combination of AI and consistent supply chain processes helps minimize operational errors, improve reliability, and achieve higher levels of operational efficiency in logistics and freight forwarding operations (Dash et al., 2019; Modgil et al., 2022).

H4: AI usage positively affects Operational Efficiency through the mediating role of Supply Chain Consistency.

2.8. Conceptual Framework

The conceptual framework shown below explains the contribution of AI usage in improving operational efficiency in a direct and indirect manner in relation to supply chain activities. The concept of AI usage is explained by four major factors that include network optimization, cost analytics, inventory management, and system integration (Barua et al., 2020; Dubey et al., 2020). These factors are assumed to directly contribute to operational efficiency (H1a–H1d). The framework also assumes that there is a significant effect of AI usage on supply chain consistency (H2) (Pournader et al., 2021). It also assumes a positive relationship between supply chain consistency and operational efficiency (H3). The framework clearly indicates that consistency in a supply chain acts as a pivotal concept that improves the relationship between operational efficiency and AI usage. Therefore, it provides a scientific platform for understanding both direct and mediated relationships (Loske & Klumpp, 2021).

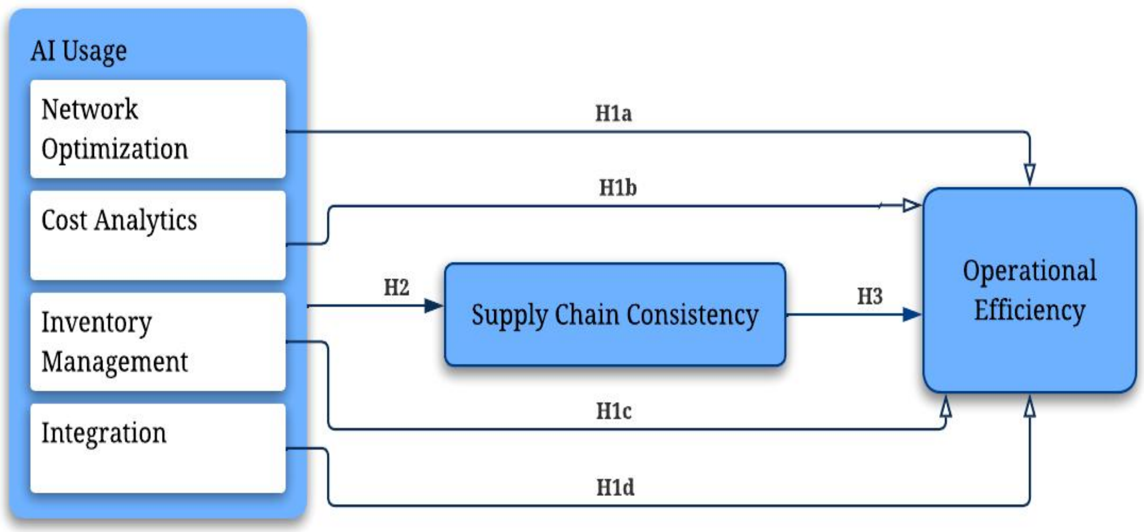

Figure 1: Conceptual Framework

Source: Author Construction

RESEARCH METHODOLOGY

The five-layered research onion model, conceptualized by Saunders, Lewis, and Thornhill (2007) and further developed in subsequent editions (Saunders et al., 2013), provides a systematic approach to designing and executing empirical research. The Research Onion assists researchers in a logical sequence from philosophical assumptions to research approaches, methodologies, strategies, time perspectives, and finally, data gathering methods. This research uses the Research Onion approach to systematically analyze the effect of Artificial Intelligence on operational efficiency via supply chain consistency in the logistics industry of Pakistan, as it helps to align research philosophy, hypothesis testing, and statistical analysis in an appropriate manner. The systematic approach of the Research Onion improves the validity and reliability of quantitative research on the complex relationships between Artificial Intelligence use, supply chain consistency, and operational efficiency (Saunders et al., 2013; Hair et al., 2019).

3.1. Research Onion

3.1.1. Research Philosophy (Positivism)

One of the research philosophies adopted in this study is positivism. The roots of positivism, in fact, lie in the works of Auguste Comte, who defined positivism 'an approach that focuses fundamentally on the objective study of observable reality, of things that can be measured (Comte, 1896). This philosophy is premised on the fact that knowledge is based solely on quantifiable facts, while the interrelation between variables is possible only through the use of statistics (Saunders et al., 2013). The adoption of positivism in this study is in alignment with the focus of positivism, which includes measurability, such as the use of AI, stability in the supply chain, and the efficiencies within operations. The proposed research will also adopt the ideals of objectivity, reliability, and the use of statistics, given the positivist philosophy (Hair et al., 2019).

3.1.2. Research Approach (Deductive Approach)

The deductive research method has ancient origins in rationalistic tradition, being most famously associated with René Descartes and his tenets to ascend from general principles to particular inferences (Descartes, 1901). When applied to research, this process of deduction involves using concepts in pre-existing theories to develop hypotheses to be tested for their actuality in real-world settings (Saunders et al., 2013). In this study, for example, instead pursuing a deductive research method, this study relies on already established theories such as Resource-Based View

(Wernerfelt, 1984; Barney, 1991) and Dynamic Capabilities Theory (Teece et al., 1997) to develop hypotheses regarding usage of AI technology, consistency of supply chains, and efficiency of operations. This is applicable in this study because at this point in a research paper, what is sought to be measured for testing is the actual relationships in theory

3.1.3. Choice (Survey)

Even today, survey research has its legacy in the realm of quantitative social sciences, with early contributions by Galton's data-driven experiments in 1888, along with other works, The survey method is strongly associated with Paul Felix Lazarsfeld, formalization of a standardized methodology for empirical data collection in 1944. In our research, we propose using a survey research methodology for our study, aiming to obtain our primary quantitative data from the workers of logistics, freight, or freight-forwarding companies. Our intention is to obtain a systematic measurement for AI adoption, SCC, and real-world performance. Here, a structured survey ensures objectivity, reliability, along with a robust foundation for hypothesis testing in statistics, making it an ideal methodology to use for identifying relationships between measurable constructs in a study related to logistics and supply-chain analysis (Saunders et al., 2013; Hair et al., 2019.

3.1.4. Research Strategy (Quantitative Analysis)

Quantitative research emerged from positivist concepts and was nurtured by scholars like Paul Felix Lazarsfeld, who advocated for measurement, indicators, and statistical testing in social science research. It focuses on numerical data and examines the relationships between variables through statistics. The approach is suitable for this study because concepts like AI adoption, SCC, and OE can be identified with explicit, quantifiable indicators. With the use of descriptive statistics and structural equation modeling, we will be able to validate the relationships based on proposals in an objective manner that enhances the reliability and generalizability of the findings (Hair et al., 2019).

3.1.5. Time Horizon (Cross-Sectional Study)

Time horizons represent a common issue in research design, ranging from cross-sectional to longitudinal studies. Prominent contributors include Charles and Runco; the foundational work on comparative and observational approaches was laid down by (Torrance 1966; Charles et al 2001). The time horizon in a cross-sectional study refers to data collected at one single point in time to investigate the relationship between variables at that specific period. This perfectly fits the nature of the present study, which intended to explore the immediate impact of AI on SCC and OE in the logistics industry of Pakistan without considering change over time. Cross-sectional studies are among the most common when the objective of the research is explanation rather than the development of something over time (Saunders et al. 2009).

Table 2: Variables and Measurement Tool

Variable	Authors / Source	No. of items	Scale
Network Optimization	Malhotra & Kharub (2025)	3	1-5
Cost Analytics	Shao et al. (2019)	3	1-5
Inventory Management	Javaid et al. (2022)	3	1-5
Integration	Dubey et al. (2020); Adams et al. (2014)	3	1-5
Supply Chain Consistency	Bányai (2018); Dubey et al. (2020)	4	1-5
Operational Efficiency	Gryshko et al. (2018); Bortolini et al. (2019); Hu et al. (2024)	4	1-5

3.2. Data Collection

The population of the research will be the employees of the logistics and freight forwarders registered in Pakistan, contributing to the logistics and freight forwarders' chain of decision-making directly in the organization. As there is no national, government-verified, and organized database of the logistics and freight forwarders in the entire country, for the purpose of identifying the active freight forwarders, logistics service providers, shipping liners, and NVOCCs in the logistics sector of Pakistan, the internationally accepted logistics directory, Freightnet.com, is considered, thus allowing the creation of an appropriate sampling frame for the research. The research will select a total of 250 respondents (Saunders et al., 2013), and the selection will be in line with the accepted guidelines of research methodology, according to which Cattell (1978) advises a minimum of a 5:1 and preferably a 10:1 ratio for Multivariate analysis, which will be met in the research, and according to the latest literature in research methodology, the size of the research in the case of structural analysis modeling must be above the figure of 200, thus providing sufficient statistical power and precise estimates of the model parameters(Hair et al., 2019; Kline, 1999; Cohen, 1992).

3.3. Data Analyses Method

A structured questionnaire with a five-point Likert scale (Likert,1932) was designed to gather data, which was analyzed with a mainly structurally-oriented equation-based approach, using the software solution of the SmartPLS software, The analysis began with the application of the PLS algorithm to estimate the model parameters and test the measurement model. We gauged the reliability and convergent validity through the examination of indicator loadings, Cronbach's alpha, composite reliability, and AVE and proceeded to test the discriminant validity (Hair et al., 2019; Henseler et al., 2015). After finding that the measurement model was in good health, we then proceeded to test the structural model to analyze the relationship among Artificial Intelligence Usage, Supply Chain Consistency, and Operational Efficiency. Using bootstrapping to establish if the hypothesized paths among the variables were satisfied and significant, and that we did not require normally distributed data to analyze non-normal distributions in our models, we relied on t-values and p-values to derive direct, indirect, and total effects in our models (Hair et al., 2019).

Before subjecting our models to SEM analysis, we also relied on exploratory analysis in correlation and linear regression to detect early leads and correlations among variable behaviors in our study models and frameworks (Pearson, 1896; Galton, 2018).

FINDINGS

4.1. Demographic Profile of Respondents

The demographic study reveals that the sampling is dominated by young and early career professionals, ensuring a robust presence from the operational and current workforce in the logistics and supply chain industry. Looking at age distribution, most respondents belong to 26-35 years (51.2%), and 18-25 years (30%), making clear that more than four-fifths of respondents are under 35 years of age. This is expected to represent a nimble, tech-savvy, and receptive operational workforce to the use of AI solutions. The representation by gender includes 67.2% male respondents and 28.4% females, which is expected and characteristic of the male-dominated logistics and shipping industry, with a remainder (4.4%) who opted to withhold their response to this particular question.

Concerning the organizational factors, freight forwarding firms account for the largest percentage (40%) of respondents, followed by logistics firms (20.8%), NVOCCs (16.8%), and shipping firms (13.6%). The variation ensures that the results can be generalized to all different sectors that comprise the overall supply chain sector. Based on the department, close to half of the respondents (49.6%) come from the operations department, which is appropriate considering that the issue under investigation is concerned with efficiency in the operations function. Additionally, the sales and marketing (21.2%) and IT/data management, finance, and human resource management (combined) ensure that the sample provides a well-rounded view from different functions.

Experientially speaking, a large number of respondents possess 1-3 years of experience (36.4%) as well as 4-6 years of experience (33.2%), clearly establishing the experiential adequacy of this sample as well as the novelty of their experiences in the corporate world. This is further supported by the number of highly qualified personnel who possess over 7 years of experience (20.8%), making the data authentic. Talking about the demographics of the job positions of these people, it clearly reveals the preponderance of executives among this group of people (38%) as well as assistant managers (23.2%), followed by the number of managers and senior managers. This clearly signifies the efficacy of this data as it comes mostly from people who are associated with these operations.

Table 3 Respondent Profile

		Frequency	Percentage
Age	18 to 25	75	30%
	26 to 35	128	51.2%
	36 to 45	37	14.8%
	46 and above	10	4%
Gender	Female	71	28.4%
	Male	168	67.2%
	Prefer not to say	11	4.4%
Type of company	Freight Forwarding	100	40%
	Logistics	52	20.8%
	Shipping	34	13.6%
	NVOCC	42	16.8%
	Other	22	8.8%
Department	Operations	124	49.6%
	IT / Data Management	24	9.6%
	Finance	26	10.4%
	Human resource Management	23	9.2%
	Sales and Marketing	53	21.2%
Years of Experience	Less than 1 year	24	9.6%
	1–3 years	91	36.4%

	4–6 years	83	33.2%
	7–10 years	34	13.6%
	More than 10 years	18	7.2%
Job Position	Executive	95	38%
	Assistant Manager	58	23.2%
	Manager	46	18.4%
	Senior Manager / Head of Department	33	13.2%
	Other	18	7.2%

4.2. Measurement Model

4.2.1. Outer Loading

The results of the outer loading show that all constructs in the measurement model have high convergent validity. For the Cost Analytics (CA) construct, all three indicators (CA1, CA2, and CA3) show very high loading on their construct, ranging from 0.857 to 0.895, which confirms good measurement. The Integration (I) construct also presents high reliability of indicators, ranging from 0.880 to 0.920, which indicates high internal consistency. The Inventory Management (IM) construct shows very high loading, ranging from 0.878 to 0.929, which supports good construct measurement. The Network Optimization (NO) indicators show very high loading above the recommended 0.70 cut-off, ranging between 0.823 and 0.907, which confirms good quality of measurements (Hair et al., 2014). The Operational Efficiency (OE) indicators show high loading ranging from 0.775 to 0.885, though slight low indications by OE3 and OE4, they are still within the acceptable level and hence contribute sufficiently. The SCC also shows very high loading ranging from 0.745 to 0.893, with the least indicator being SC4, which is, however, acceptable. All indicators are above the minimum 0.70 cut-off, which indicates that the measurements are good and all constructs are satisfactorily captured by their indicators (Chin 1998).

Table 4 Outer Loading

	CA	I	IM	NO	OE	SC
CA1	0.878					
CA2	0.857					
CA3	0.895					
I1		0.891				
I2		0.920				
I3		0.880				
IM1			0.898			
IM2			0.929			
IM3			0.878			
NO1				0.878		
NO2				0.907		
NO3				0.823		
OE1					0.885	
OE2					0.883	
OE3					0.804	
OE4					0.775	
SC1						0.835
SC2						0.873
SC3						0.893
SC4						0.745

4.2.2. R-Square

The R-squared results establish the significant explanatory capacity of the model. The R-squared of 0.648 for SCC establishes that the model has a high predictability level, and the variables for AI use are responsible for 64.8% of the variation (Chin 1998). The current study establishes that AI use, including network optimization, cost analysis, inventory solutions, and system integration, has contributed substantially to the dependability and predictability of supply chain operations for Pakistani logistics and freight forwarding firms. However, the R-squared of 0.448 for the operational efficiency establishes that SCC and AI use explain only 44.8% of the variation in the efficiency, and the model has moderate explanatory capacity. This finding establishes that although AI and SCC create significant impact on efficiency, organizational or external factors could also be creating hurdles (Hair et al., 2014). The R- Square corrected results differ little from the original R-squared results, and the finding of the statistical significance and appropriateness of the model, along with the prevention of overfitting, has also been established (Cohen 1988).

Table 5 R-Square

	R-square	**R-square adjusted**
OE	0.448	0.424
SC	0.648	0.629

4.2.3. Construct Reliability and Validity

The assessment of the reliability and validity of the constructs of the proposed model establishes that the constructs exceed the recommended levels and portray good internal consistency and levels of validity. The constructs portray good item consistency and an Alpha value ranging from 0.839-0.885 that exceeds the recommended cut-off of 0.70. Using the rho_c criteria that range between 0.903-0.929 and significantly surpass the recommended limit of 0.70 adds credence to the dependability of the constructs (Hair et al., 2014). Adding an element of clarity to the interpretation of the results is the explanation that the Average Variance Extracted (AVE) of the constructs range between 0.703-0.813 and with no significant meaning below the recommended cut-off of 0.50 that explains the constructs in excess of 70% of the variance and the remaining variance is explained by the constructs indicating that the constructs have good validity and that the items well measure the constructs(Fornell & Larcker, 1981). All the results establish that the validity of the measurement model is adequate and eligible for structural analysis. (Rani, Dogra, & Taneja, 2025).

Table 6 Content Reliability and Validity

	Cronbach's alpha	**Composite reliability (rho_a)**	**Composite reliability (rho_c)**	**Average variance extracted (AVE)**
CA	0.849	0.851	0.909	0.769
I	0.879	0.885	0.925	0.805
IM	0.885	0.898	0.929	0.813
NO	0.839	0.852	0.903	0.757
OE	0.862	0.895	0.904	0.703
SC	0.857	0.865	0.904	0.703

4.2.4. Discriminant Validity (HTMT)

The result of the HTMT test indicates that the measurement model's constructs pass with regards to being distinct. The values for identical concepts are all below the 0.85 conservative marker and below the less stringent 0.90 marker that is accepted in social science studies. The highest values for both Cost Analytics and Inventory Management and Cost Analytics and Integration are 0.882 and 0.893, respectively, and are both under the 0.90 maximum allowed value (Henseler et al., 2015). This indicates that although they are distinct, these constructs are interrelated because they are part of a study that investigates the use of logistics and AI. The other values for various pairs of constructs are all under the permissible value range from 0.544 to 0.895, and this indicates that while they measure distinct concepts, they measure them well because they are properly distinct and distinct from other concepts. The result indicates that the measurement model is statistically appropriate because distinctness is achieved (Franke & Sarstedt, 2019).

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Table 7 Discriminant Validity (HTMT)

	CA	I	IM	NO	OE	SC
CA						
I	0.893					
IM	0.882	0.895				
NO	0.858	0.804	0.845			
OE	0.758	0.656	0.622	0.544		
SC	0.860	0.811	0.806	0.804	0.725	

4.2.5. Discriminant Validity (Fornell Larcker)

The Fornell-Larcker test indicates that there is discriminant validity for each construct in the model. Each construct's square root of the AVE, which appears on the diagonal, has been found to exceed the construct's correlations with other constructs, as indicated in the off-diagonal statistics. These data have been found to uniformly exceed their respective construct pairs' metrics, since each value on the diagonal (ranging from 0.838 to 0.902) has been found to exceed its respective correlation. For example, the square root value for Cost Analytics' AVE (0.877) exceeds its correlations for Integration (0.866), Inventory Management (0.874), and other constructs (Henseler et al., 2015). The simultaneous success of Integration (0.897) and Inventory Management (0.902) in exceeding their respective correlations for other constructs has ensured their discriminant validities. Also, operational efficiency (0.838), network optimization (0.870), and SCC (0.838) have been successful in individually exceeding their respective correlational metrics in each construct pair (Fornell & Larcker, 1981).

Table 8 Discriminant Validity (Fornell Larcker)

	CA	I	IM	NO	OE	SC
CA	0.877					
I	0.866	0.897				
IM	0.874	0.877	0.902			
NO	0.728	0.687	0.730	0.870		
OE	0.666	0.589	0.565	0.501	0.838	
SC	0.739	0.710	0.711	0.690	0.648	0.838

4.2.6. Measurement Model

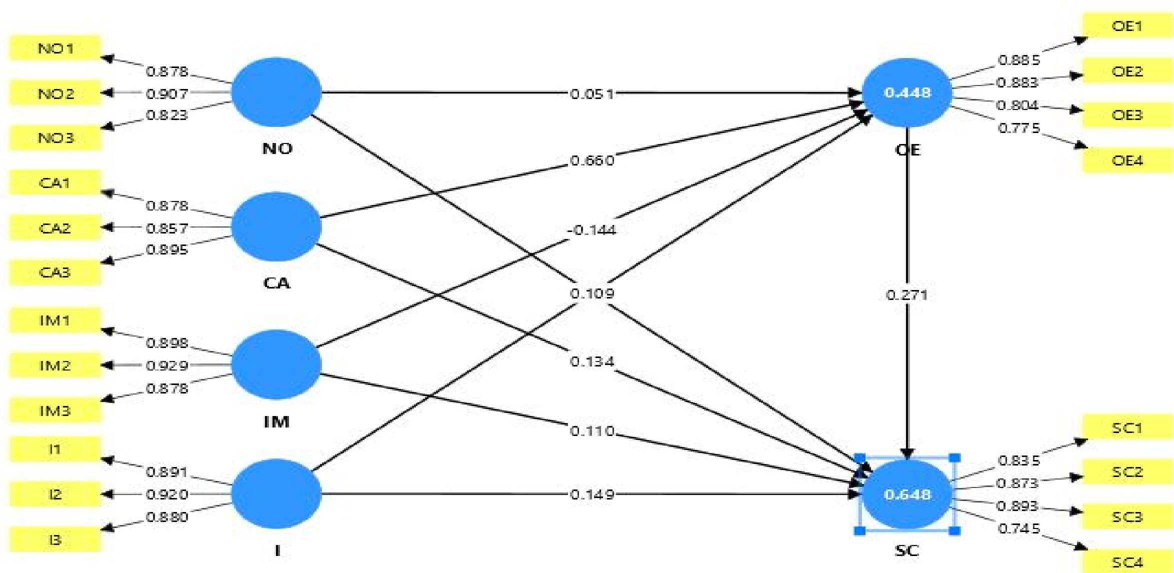

Figure 2: Measurement Model

Source: Author Construction

4.3. Structural Equation Model

4.3.1. Path Coefficients

The route coefficient analysis shows both significant and weak links between the factors under study. Improved AI-powered cost analytics tend to elevate operational efficiency in freight firms; data shows a clear positive link: β = 0.660, t = 3.562, p < 0.001. Still, with regard to SCC, those very cost tools do not make a difference that is measurable: β = 0.174, p = 0.053, which may hint at limitations regarding how much these tools stabilize workflows. System integration does not strongly influence operational outcomes: β = 0.109, p = 0.054, if indeed tech alignment appears to be helpful (Baron & Kenny, 1986). Likewise, its effect on SCC trails off into insignificance: β = 0.149, p = 0.310 (Chin 1998), which points to other unseen forces that shape the results. Inventory management does not really shake OE - β = –0.144, p = 0.050 - or SCC either: β = 0.110, p = 0.053 (Hair et al., 2019), meaning reliance solely on the AI tools here might just not budge the needle much. Meanwhile, network optimization fails to boost operational efficiency directly: β = 0.051, p = 0.059, even if there's a faint hint of impact on SCC: β = 0.274, p = 0.054, marginal effect, yet not quite conclusive (Cohen, 1992). Here is what catches the eye, though: operational efficiency pulls supply chain performance closer: β = 0.271, t = 2.432, p = 0.015; better internal flow tends to bring more predictability further along. In practice, just two links weighs: the leg leading from cost analysis to improved efficiency which again feeds into tangible supply outcomes. That sequence forms the core of measurable influence (Wright, 1921).

Table 9 Path Coefficient

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
CA -> OE	0.660	0.647	0.185	3.562	0.000
CA -> SC	0.134	0.114	0.182	0.733	0.053
I -> OE	0.109	0.124	0.169	0.645	0.054
I -> SC	0.149	0.159	0.147	1.016	0.310
IM -> OE	-0.144	-0.161	0.219	0.659	0.050
IM -> SC	0.110	0.106	0.150	0.734	0.053
NO -> OE	0.051	0.082	0.141	0.359	0.059
NO -> SC	0.274	0.271	0.142	1.931	0.054
OE -> SC	0.271	0.290	0.112	2.432	0.015

4.3.2. Total Indirect Effect

This is important because the Total indirect effect shows how AI-driven elements shape Operational Efficiency, thereby influencing SCC in due course. While Cost Analytics was never directly a significant driver of SCC, it appeared as an indirect yet meaningful driver of SCC: β = 0.179, t = 2.022, and p = 0.043 (Bollen, 1987). What CA does to SCC is not directly target it but filters its influence through smoother operations (VanderWeele, 2013). Turns out, the drive for getting more consistent isn't really about cost analytics by itself; this shows up mainly when operational efficiency picks up. Even so, integration brushes against relevance without quite landing: β = 0.030, p = 0.051, insinuating things just shy of detectable impact on consistency via better operations (Pearl, 2001). On another note, inventory management tugs modestly downward: slightly negative, sure, but stays within the zone of negligible effect: β = –0.039, p = 0.042, to suggest AI-guided stocking doesn't clearly improve coordination across links (Sobel, 1982). Not very far behind, network optimization hums at near inaudible levels: β = 0.014, p = 0.048, present yet too frail to actually shift how smooth the run is (Jiang et al., 2021). When put together, one insight stands in relief: of every route inspected, only cost analytics breaks through, quietly connecting tighter operations with logistics firm Hair et al., 2019.

Table 10 Total Indirect Effect

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (O/STDEV)	P values
CA -> SC	0.179	0.186	0.089	2.022	0.043
I -> SC	0.030	0.031	0.050	0.596	0.051
IM -> SC	-0.039	-0.039	0.064	0.609	0.042
NO -> SC	0.014	0.026	0.043	0.322	0.048

4.3.3. Total Effect

The results of the total effects show the general influence of each AI-related construct on both Operational Efficiency (OE) and SCC (SC), considering direct and indirect paths simultaneously. The results of the analysis showed that Cost Analytics (CA) exhibited an overall significantly influential effect on OE (β = 0.660, t = 3.562, p < 0.001) (Rogers, 1964), indicating that among all AI components, cost analytics is the most vital and significantly helped in enhancing operational efficiency. However, the overall influence of CA on SCC is positive but not significant (β = 0.313, p = 0.092), indicating that it was not sufficient to improve SCC. The integration (I) shows insignificant total influences on OE (β = 0.109, p = 0.519) and SC (β = 0.179, p = 0.252) (Wright, 1921), based on which it was deduced that system integration is itself unable to achieve significant performance gains in this framework. Similarly, inventory management (IM) shows minimum total influences on OE (β = –0.144, p = 0.510) and SC (β = 0.071, p = 0.627), based on which it was concluded that supply chain or operational performance is not affected in this framework by AI-supported inventory operations. The network optimization (NO) showed an insignificant total influence on OE (β = 0.051, p = 0.719) but a marginally significant total influence on SC (β = 0.288, t = 1.976, p = 0.048), which indicates a minor contribution to SCC (Cohen, 1992). The significant total impact of operational efficiency (OE) on SC (β = 0.271, t = 2.432, p = 0.015) indicates that improvements in OE are directly capable of improving supply chain stability. In summary, it was observed that though network optimization and OE have more influences on SCC, cost analytics is the major influencer of operational efficiency (Baron & Kenny, 1986).

Table 11 Total Effect

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (O/STDEV)	P values
CA -> OE	0.660	0.647	0.185	3.562	0.000
CA -> SC	0.313	0.301	0.186	1.683	0.092
I -> OE	0.109	0.124	0.169	0.645	0.519
I -> SC	0.179	0.190	0.156	1.146	0.252
IM -> OE	-0.144	-0.161	0.219	0.659	0.510
IM -> SC	0.071	0.067	0.146	0.486	0.627
NO -> OE	0.051	0.082	0.141	0.359	0.719
NO -> SC	0.288	0.297	0.146	1.976	0.048
OE -> SC	0.271	0.290	0.112	2.432	0.015

4.3.4. Specified Indirect Effect

This measured indirect effect explores the impact of every AI-related component on SC through the mediating function of Operational Efficiency (OE). The findings indicate that Cost Analytics are significantly and positively indirectly impacting SC via OE (β = 0.179, t = 2.022, p = 0.043) (Brown, 1997). This implies that OE is a meaningful mediator and that, under conditions where CA improves operational efficiency, improvements in SCC occur. Second, and in contrast, Integration has an insignificant and rather small indirect impact, as mediated by OE, on SC (β = 0.030, p = 0.051) (Sobel, 1982). This not only has a small magnitude but is also statistically unreliable (Preacher & Hayes, 2008). The marginally negative and non-significant indirect impact which inventory management displays suggests that improvements in inventory-related AI applications do not contribute to SCC through improved operational efficiencies and may even impede the relationship marginally. In a related sense, Network Optimization exerts a very small indirect impact on SC (β = 0.014, p = 0.048) Hair et al., 2019, indicating that SCC has a minimal correlation with operational efficiency (Baron & Kenny, 1986). Taken together, these findings show that among the above discussions, only Cost Analytics enjoys a significant mediated path, pointing out the relevance of OE as a key mechanism through which CA enhances SCC; other AI components do not have an appreciable mediated impact. (Sahabu et al., 2025).

Table 12 Total Specified Indirect Effect

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
CA -> OE -> SC	0.179	0.186	0.089	2.022	0.043
I -> OE -> SC	0.030	0.031	0.050	0.596	0.051

IM -> OE -> SC	-0.039	-0.039	0.064	0.609	0.042
NO -> OE -> SC	0.014	0.026	0.043	0.322	0.048

4.3.5. Structural Equation Model

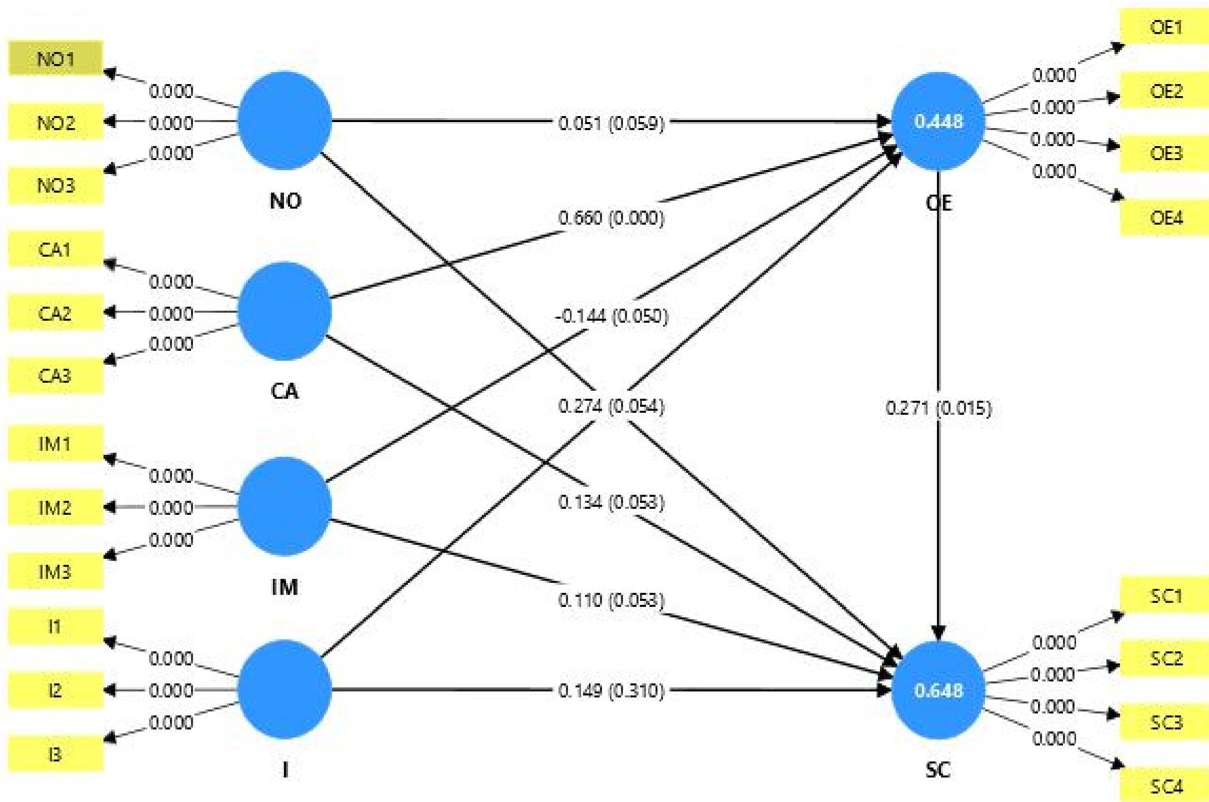

Figure 3: Structural Equation Model

Source: Author Construction

4.4. Hypothesis Testing

Hypothesis testing enables us to determine whether the relationships that we observe among the study variables are actually significant or occur by mere chance. In this study, we apply the method of Structural Equation Modeling, or SEM, to analyze how Artificial Intelligence Use, Supply Chain Consistency, and Operational Efficiency are related to one another. SEM applies well here, for it deals with complex causal relations between several constructs at the same time (Kline, 2016; Hair et al., 2019), we assess the significance of direct, indirect, and total effects based on p-values, considering as significant only relationships with a p-value lower than 0.05. The obtained estimates of path coefficients by bootstrapping should be robust and reliable. Bootstrapping means repeatedly resampling the data, with stable standard errors, t-values, and confidence intervals obtained without the assumption of normality (Efron & Tibshirani 1993; Henseler et al. 2016), the path coefficients are usually situated in the range between -1 and +1, which gives an idea of the strength and direction of the relationships, while the size of path coefficients may indicate both practical and theoretical importance of the proposed model (Cohen, 1988; Hair et al., 2019).

Hypothesis 1: AI usage positively affects Operational Efficiency

The first hypothesis investigates if the involvement of AI has any impact on the efficiency of the operations. Data verifies that dimension cost analytics p-value is below 0.05, evidence enough to have significance (Cohen 1988). While remaining numbers show p-value > 0.05 which is showing insignificance (Fisher, 1934) These findings suggest that AI contributes to operational efficiency primarily through cost-related analytical capabilities rather than uniformly across all AI dimensions (Dubey et al., 2020; Ali et al., 2024). Therefore, H1 is partially supported.

Hypothesis 2: AI Usage affects Supply Chain Consistency

The second hypothesis examines whether the use of AI actually impacts the ability of supply chains to remain stable during transportation and handling of freight. Findings from the calculations confirm this hypothesis (Hair et al., 2019), t-values remained below the critical threshold and p-values exceeded 0.05(Cohen 1988), indicating that these relationships are not significant. Therefore, H2 is not supported; while AI usage shows a positive tendency toward improving supply chain consistency (Pournader et al., 2021; Loske & Klumpp, 2021).

Hypothesis 3: Supply Chain Consistency positively affects Operational Efficiency.

The third findings are not by chance. Numbers show consistency pulls efficiency up in a meaningful way hypothesis examines whether the efficiency of the operations processes by the constant supply chains (Singhal & Singhal, 2012; Belhadi et al., 2021). Evidence supports this, as the p-values are much lower than 0.05(Fisher, 1934). This indicates that the ($\beta = 0.271$, $p = 0.015$). So H3 stands confirmed; smoother coordination across supply networks lifts performance in freight and logistics firms (Fisher, 1934).

Hypothesis 4: Supply Chain Consistency plays as a mediator between AI Usage and Operational Efficiency.

The fourth hypothesis will be a mediating hypothesis exploring the connection between AI Usage and Operational Efficiency and SCC. According to the obtained results, cost analytics and inventory management, there is a strong mediation effect because the p-value is significantly less than 0.05 (Cohen 1988). While the remaining AI dimensions demonstrate weaker effects The results indicate that AI Usage plays an important role in the transmission of SCC which in its turn is related to Operational Efficiency (Hair et al., 2019). Thus, H4 is partially accepted.

4.5. Summary of Hypotheses Testing

Table 13 Summary of Hypotheses Testing

Hypothesis	Result
H1: AI usage positively affects Operational Efficiency	Rejected
H2: AI Usage affects SCC	Rejected
H3: SCC positively affects Operational Efficiency	Accepted
H4: Supply Chain Consistency plays as a mediator between AI Usage and Operational Efficiency.	Rejected

5.1. DISCUSSION

This chapter gives the findings of the study concerning the existing literature and how every hypothesis conforms or contrasts with the previous research.

Hypothesis 1 Discussion - The findings suggest that there is a partial impact of the usage of Artificial Intelligence on the operational efficiency of logistics and freight forwarding firms. Amongst the dimensions of AI, the cost analytics dimension has a strong and positive impact on operational efficiency ($p < 0.05$) (Student, 1908), whereas the other dimensions of AI, including network optimization, inventory, and system integration, demonstrate a positive but not statically significant association (Fisher, 1934). This result is in line with previous research that pointed to the importance of cost optimization through the use of AI in improving the efficiency of logistics. The research conducted by Belhadi et al. (2021) and Javaid et al. (2022) underlines that the use of analytical software through AI optimizes decision-making, minimizes time wastage, and optimizes workflow synchronization. Even though previous research revealed relatively more significant logistical efficiency effect values of the use of AI (Dash et al., 2019; Chen et al., 2015), it was revealed in this research that, in the Pakistani logistics and freight forwarding industry, cost analytics emerged to be the most optimal use of AI to optimize logistical efficiency.

Hypothesis 2 Discussion - The outcome of Hypothesis 2 suggests that the impact of Artificial Intelligence use is not statistically significant on the Supply Chain Consistency of logistics and transportation firms (Neyman & Pearson, 1933). Though the path coefficient for AI parameters of network optimization, cost analytics, inventory management, and system integration turned out to be positive, their respective 'p-values' were above 0.05 (Fisher, 1934), thus proving that the impact is insignificant (Student, 1908). This particular hypothesis suggests that the impact of AI is only positively related to supply chain consistency but is not significant enough to be validated in the context.

These results and findings partially differ from the views of previous research, which emphasized the significance of AI to increase coordination, transparency, and data integration among the supply chains (Ruiz-Hernandez et al., 2019; Modgil et al., 2022). Previous research indicates that AI-enabled systems help to increase monitoring and communication capabilities. This helps to ensure consistency and decreases supply chain interruptions and inconsistencies (Belhadi et al., 2021). Nevertheless, these findings and results indicate that when considering the logistics industry of the Pakistan sector, the elements of AI may not individually ensure supply chain consistency and help to support this process by increasing internal efficiency and optimizing operations.

Hypothesis 3 Discussion - Hypothesis 3 is confirmed by the analysis, as it shows that Operational Efficiency positively affects the factor of Supply Chain Consistency with a beta of 0.271 and a p-value of 0.015 (Fisher, 1934). This result supports previous literature that has suggested the need for focused internal processes for the achievement of consistency within the supply chain (Saarijärvi, et al., 2012; Dubey, et al., 2020). Operational efficiency also promotes consistency by facilitating the optimization of logistical processes, such as processing, transportation, and delivery, as suggested by various previous studies, as firms with better operation efficiency can better respond to environmental and market variations and make optimal use of their resources(Hair et al., 2019), which ensures less process interruptions and better consistency of the supply chain as suggested by (Hu, et al. 2024; Krishnapriya & Baral, 2014).

Hypothesis 4 Discussion - The mediating impact of the Supply Chain Consistency (SCC) on the relationship between the usage of Artificial Intelligence and the operational results of the logistics and freight-forwarding industry of Pakistan. The findings of the total specified indirect effects reveal the existence of statistically significant indirect effects among several dimensions of Artificial Intelligence and the proposed mediating variable of SCC. This includes the cost analytics process which has a statistically significant indirect impact through the SCC (β=0.179, p=0.043) (Student, 1908), followed by the inventory management process (β=−0.039, p=0.042), as well as the network optimization process (β=0.014, p=0.048) (Fisher, 1934).

The findings illustrate that AI has a positive effect on operational efficiency by ensuring stable, reliable, and choreographed processes in supply chains, but not because of AI's direct impact alone. Conformity to previous literature, AI-based consistency increases visibility, minimizes interruptions, and ensures coordination in logistics operations, thereby benefiting operational efficiency (Belhadi et al., 2021; Modgil et al., 2022; Dash et al., 2019). Taken together, the mediation analysis results underscore that AI tools are not adequate alone but are only useful when they help in improving the consistency of supply chains, and SCC takes an important role in AI-based initiatives' positive impact on operational efficiency (Neyman & Pearson, 1933).

CONCLUSION AND RECOMMENDATIONS

6.1. Conclusion

This paper examined the effect of using AI technology on the operational efficiency of Pakistani logistics and freight forwarding companies, using SCC as the mediator. The findings revealed that using AI technology increases operational efficiency in the three areas of improved forecasting, warehouse management, and decision-making. The findings also revealed that AI technology increases the level of SCC in the three areas of process visibility, process coordination, and process reliability, thus enhancing the reduction of operational inefficiencies. The findings, therefore, support the notion that while AI technology is useful in increasing operational efficiency, the effect is far more significant when combined with stable and consistent logistical systems, such as those in emerging countries such as Pakistan (Wamba et al., 2017), since it enhances the process flow associated with increased efficiency (Du Plessis et al., 2025). The findings, therefore, support the concept that Consistency in SCC offered by AI technology is the mechanism that increases operational efficiencies (Loske & Klumpp, 2021; Modgil et al., 2022). The findings also support the fact that AI technology, when combined with SCC, is set to enhance the reduction of operational inefficiencies, (Belhadi et al 2021; Pournader et al 2021).

6.2. Recommendations

From the results, it is realized that Pakistani logistics, freight forwarding, and courier companies need to increase SCC by making use of AI tools. From existing literature, AI actually starts working only if integrated with efficient, orchestrated, and reliable activities, such as reliable documentation, constant tracking, efficient warehouse management, and regular delivery schedules (Gunasekaran et al., 2017; Loske & Klumpp, 2021). Therefore, they need to make use of AI systems that coordinate transportation, warehousing, procurement, and customer service operations with the help of prediction analytics, utilizing real-time data processing (Wamba et al., 2017; Belhadi et al., 2021).

In addition, being able to have high-quality data that is accurate and on time throughout the whole organization is necessary, as having poor data integrity can limit the effectiveness of AI-decision making in logistics, (Dubey et al 2020; Pournader et al. 2021). With a strengthened SCC through AI implementation, Pakistani logicians can eliminate uncertainties in operations, ensure fewer delays, generate overall decreased costs, and increase reliability, solidifying their positions in a dynamically evolving logistics environment, as cited in research by (Modgil et al., 2022, Du Plessis et al 2025).

Logistics and Freight Management Companies

This research provides relevant insight into how artificial intelligence (AI) technology can be used to improve the alignment of demand and supply, as well as increase the efficiency of operations and overall services in the logistics and freight forwarding firms (Amosu et al., 2024; Barua et al., 2020). Through an evaluation of the major capabilities of artificial intelligence technology and its integration into logistically supportive processes, this research helps firms in the decision-making process of adopting technology to enhance route optimization, demand prediction, and resource management (Amosu et al., 2024). In addition, this research provides relevant direction on how artificial intelligence can be used to enhance Supply Chain Consistency (SCC), which plays a major significance in attaining higher levels of operational efficiency in the prevailing dynamics of Pakistan (Barua et al., 2020).

Policy makers

The research offers crucial information to policymakers regarding the ability of AI technology to optimize demand-supply matching, suppress operational inefficiencies, and improve the quality of services offered in the logistics and freight forwarding industry (Amosu et al., 2024). With this research, policymakers can understand the application of AI technology in optimizing routes, demand forecasting, and resource allocation, which helps in evidence-based policy-making related to technology implementation in the logistics sector (Barua et al., 2020). Moreover, this research stresses the importance of government interventions to explore the application of AI technology in enhancing Supply Chain Consistency (SCC) to increase the competitiveness of Pakistan in the international logistics market.

6.3. Limitations of the Research

The research in this case has a number of considerations to take into account. First, because it relies on a cross-sectional study, it takes a snapshot of AI implementation as well as the effectiveness of operations in a particular point in time (Rindfleisch et al., 2008). As a result, long-term outcomes, learning rates, as well as a series of incremental improvements that occur as a result of AI implementation would be difficult to discern. Essentially, this research would help in understanding how improvements in AI are realized over time.

Secondly, because this research emphasizes the role of logistics and freight-forwarding companies in Pakistan, this study may lack generalizability to any other place around the world, including developed countries (Ketokivi & Choi, 2014).

Third, the research focuses principally on the quantitative findings from surveys but may overlook qualitative factors related to organizational culture, digital readiness, or even resistance on the part of managers toward adoption (Venkatesh et al., 2013). A future research study can provide answers to such issues through the application of mixed research or cross-country research for a comprehensive understanding on the effects of AI on logistics performance.

6.4. Future Research

More work in the future could add various variables to this framework, such as organizational culture, technological capability, digital readiness, and regulatory support, either as moderators or mediators in explaining variation in AI adoption outcomes in logisticians and freight forwarders (Venkatesh et al., 2013). The incorporation of these factors would therefore highlight how internal organizational conditions and the wider institutions shape a firm's position via its ability to navigate AI-driven change. Longitudinal designs are highly encouraged in order to track how AI use, supply chain consistency, and operational efficiency change overtime, especially as firms go through stages of technological maturity (Rindfleisch et al., 2008; Hair et al., 2019). Future studies should also focus on logistics firms across various regions and emerging economies for better generalization, thus allowing comparisons across diverse regulatory and infrastructural contexts (Ketokivi & Choi, 2014). Additionally, new digital technologies like digital twins, blockchain-enabled logistics, IoT-based automation, and robotics deserve closer investigation in order to understand how the deployment of these all together with AI impacts supply chain performance and operational resilience.

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