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AI-Driven Logistics and Supply Chain Performance: Evidence from Saudi Arabia

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Abstract
In spite of the rapid digital transformation, the logistics and supply chain systems still have considerable cost management, delivery delays and coordination inefficiencies. This paper examines the effects of artificial intelligence (AI) implementation on logistics and supply chain operations in the context of Saudi Arabia, which faces tremendous change under Vision 2030. Empirical research design is used, based on quantitative data gathered as a result of structured surveys of logistics companies, and secondary information sources in the industry. The analysis employs statistical and econometric methods, such as multiple regression analysis, and Partial Least Squares Structural Equation Modeling (PLS-SEM) to analyze the connection between AI adoption and the key performance indicators. The results indicate that AI-powered technologies (i.e., automation, predictive analytics and intelligent decision-support systems) have a substantial positive impact on logistics performance, as they lower costs of operations, enhance efficiency of delivery times and promote productivity of the entire system. The findings also indicate a high test statistic value and have a high level of reliability of the model, and the existence of a positive AI impact on optimizing supply chain activities. This study will be useful as the literature base on the efficacy of AI in performance in logistics depends on region-specific empirical data, which is critically lacking in the literature on the topic concerning emerging economies. The results provide useful knowledge to stakeholders and policymakers in the industry to expedite AI adoption within supply chain systems to enhance competitiveness and operational agility in the Saudi logistics industry.

Keywords:
Artificial Intelligence, Logistics Performance, Supply Chain Management, Saudi Arabia, Automation, Smart Logistics, Data Analytics.

1. Introduction

The blistering development of artificial intelligence (AI) technologies has tremendously changed the world of the logistics and supply chain management, allowing organizations to improve their efficiency of operations, the precision of decision-making, and the quality of offered services. Real-time visibility, demand prediction, and efficient allocation of resources within logistics networks have become simpler with the integration of AI-powered tools, including predictive analytics, machine learning algorithms, and intelligent automation systems [1], [2]. The recent years have witnessed a rise in the use of AI following the growing sophistication of global supply chains and the necessity to have a resilient and agile logistics that are able to adapt to the dynamic market conditions [3], [4]. Moreover, the advent of the digital supply chain ecosystems, which digital big data analytics and Industry 4.0 can facilitate, has brought about fresh possibilities of optimizing the performance and lowering the costs [5], [6].The logistics industry in Saudi Arabia is going through an important change due to the national project, the Vision 2030 that will see the country be a global logistics hub linking Asia, Europe and Africa. A lot of resources have been pumped into digital infrastructure, smart ports, and sophisticated transportation systems by the government in order to improve the efficiency and competitiveness of the supply chain [7], [8]. The application of AI in the field of logistics is becoming more and more accepted as an enabler of these goals, specifically in the area of increasing delivery efficiency, decreasing operational expenses, and increasing the overall supply chain resilience [9], [10]. Irrespective of these improvements, the utilization of AI technologies within the context of logistics companies in Saudi Arabia is still not uniform, and its tangible effect on the performance outcomes is not thoroughly comprehended yet. Even though role of big data analytics, digital transformation, and new technologies in supply chain management has been thoroughly covered by previous research, much of the literature is still abstract or theoretical [11], [12]. Most of the current research is dedicated to the possible advantages of AI without empirical support of the research with concrete data and models. Furthermore, the absence of region-specific studies investigating the usefulness of AI adoption in enhancing the performance of logistics in emerging markets, like Saudi Arabia, is also noticed [13], [14]. The gap presents the necessity of the empirical research that will estimate the correlation between AI-practices and the main logistics performance indicators.In a bid to fill this gap, the main aim of this research will be to assess the effect of adoption of AI on the performance of logistics and supply chain in Saudi Arabia through an empirical research method. Particularly, the research has the objective to quantify the effects of AI-driven capabilities on such key performance indicators as cost effectiveness, time to delivery and operational performance. In accordance with this purpose, the following research question should be examined: Do artificial intelligence adoption dramatically increase the indicators of logistics performance in the operations of the supply chain? The study has a variety of implications on existing body of knowledge. First, it brings empirical data of AI adoption with logistics performance applying quantitative methods of modeling, such as regression analysis and PLS-SEM. Second, it provides region-based information about Saudi Arabian logistics industry, a field that has been scarcely addressed in the previous literature. Third, the research connects the gaps in the literature between the theoretical approach and real-world application by providing the connection between AI technologies and the quantifiable results of performance.This work contributes greatly to the literature because it does not discuss the concept in detail but rather presents an empirical analysis of the use of AI in logistics systems, based on data. The research provides a precise and measurable connection between AI technologies and the supply chain efficiency by combining statistical modelling with the real-life performance metrics. Compared to previous research, which highlights the overall digital transformation, the current work is more focused on quantifiable logistics results in the Saudi Arabian setting, thus providing academic and practical significance to the stakeholders of the industry and policymakers interested in improving supply chain performance by using AI-based solutions.

2. Literature Review

Artificial intelligence (AI) has become a revolutionary strategy to enhance efficiency and quality of operations, decision-making, and system performance in the context of supply chain management. The AI technologies like machine learning, predictive analytics, and intelligent automation have helped organizations to drive more accurate demand forecasting, optimized inventory management, and supported logistics operations [1], [2]. These abilities enable companies to handle large masses of information in real-time, resulting in enhanced visibility and responsiveness in supply chain networks. Previous research has also indicated that AI-based systems can be instrumental in terms of supply chain agility and resiliency, especially during complex and unpredictable conditions [3], [4]. Moreover, the implementation of smart logistics, such as autonomous transport systems and AI-based warehouse management, has also helped lessen the involvement of humans and enhance operational accuracy [5], [6]. As well as the technological progress, the importance of data-driven decision-making in supply chains has become more and more popular. Integration of big data analytics and AI have proven to enhance coordination between supply chain partners and improve collaboration as well as facilitate real-time optimization of logistics operations [7], [8]. There is also an AI application in logistics: optimal route, demand planning, and risk management allow firms to react positively to disruptions and fluctuating market conditions [9], [10]. Consequently, AI is progressively being regarded as a key facilitator of digital supply chain revolution, which helps to achieve a higher efficiency, adaptability, and competitiveness within the international markets.

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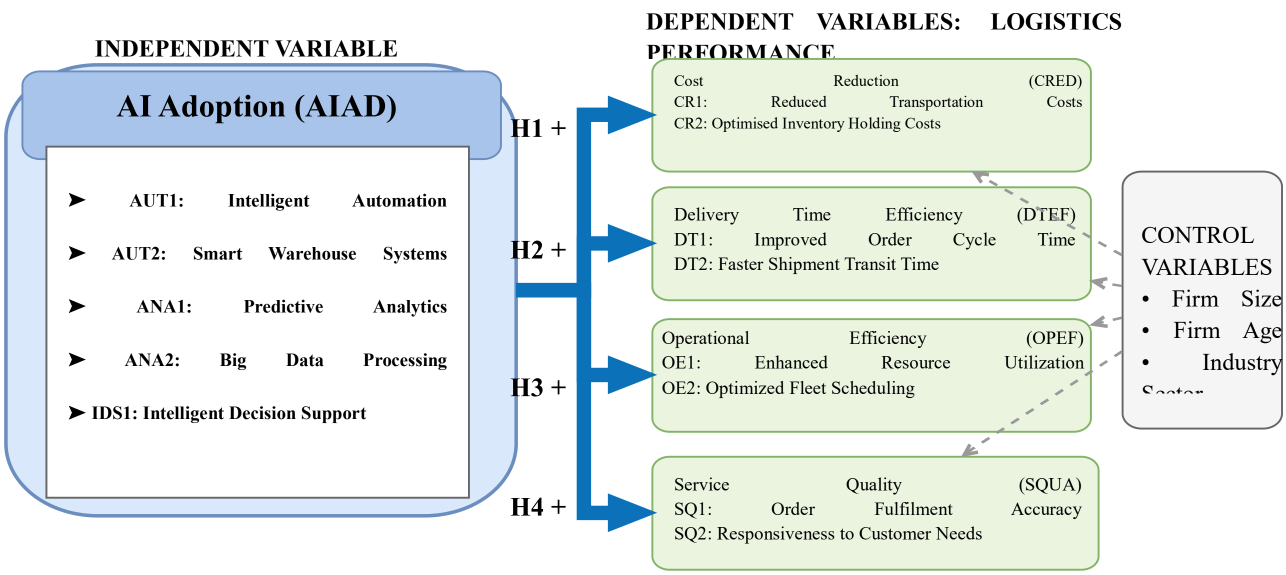
One of the most important areas of supply chain management is logistics performance measurement as it provides the foundation on which the effectiveness of operations can be assessed, and the areas of improvement can be identified. Conventional performance indicators like cost efficiency, delivery time, inventory turnover, and the service level are still important indicators to measure the performance of logistics [11]. Cost efficiency is an indicator of organizations capability in reducing the cost of operation and yet end up satisfying the quality of services, whereas delivery time is the speediness and stability of organizational order fulfilment procedures. Inventory turnover shows the efficiency with which the inventory is managed and used and service level is the extent to which the customer expectations are fulfilled. Past studies have proved that the integration of modern technologies, such as AI and analytics, can have a positive impact on these performance indicators by improving the coordination of operations and minimizing inefficiencies [12], [13].

Although the research on AI and supply chain management is increasing, the majority of researches are mainly concerned with conceptual frameworks, theoretical models or generalized research without offering empirical validation. Although current studies have recognized the importance of AI in enhancing the performance of logistics, quantitative data that can prove a direct influence of this technology on key performance indicators in practice is scarce [14]. In addition, most research is being done in developed economies and little focus is being made on emerging economies like Saudi Arabia where the logistics is an emerging sector which is changing very fast due to national transformation efforts.Despite the fact that a considerable amount of existing studies already conducted research on the importance of AI, big data analytics, and digital technologies in supply chain management, there are still significant gaps in the empirical validation of their influence on the logistics performance. Specifically, one can notice a shortage of the studies, which have a region-specific focus and provide a quantitative evaluation of the impact of AI adoption on crucial logistics performance metrics, including cost-efficiency, delivery time, turnover of inventory, and service levels in the Saudi Arabian context. Moreover, there is limited use of statistical and econometric models to find out the causal correlation between AI-inspired practices and performance outcomes because the available studies tend to use conceptual discussions or qualitative understanding. This demonstrates the necessity of the comprehensive empirical study that will combine real-life data with the quantitative modeling methods to determine the success of AI in improving logistics and supply chain performance.

3. Conceptual Framework and Hypotheses

The theoretical framework of the present study will be chosen to test the effect of the introduction of the artificial intelligence (AI) on the performance of logistics and supply chains. The main independent variable is the adoption of AI, which includes some of the main technological capabilities, including automation, predictive analytics, and intelligent decision-support systems. These technologies help organizations to work with large amounts of data, optimize the work of logistics, and improve the accuracy of decision-making, which contributes to better outcomes of the supply chain as a whole. Logistics performance is considered to be a multidimensional depended construct, which is assessed using four key indicators: cost reduction, efficiency in delivery time, operational efficiency and quality of the service. Cost saving is an indication of the capability of AI powered systems to reduce transportation, inventories, and operating expenses in the form of optimal resource use. Delivery time efficiency reflects the efficiency of order processing and transportation speed gained by predictive analytics and real-time tracking systems. Operational efficiency: this is the efficiency of logistics processes such as management of warehouses, routing, and coordination in the supply chain. Service quality checks on the degree of fulfilment of the expectations of customers in terms of reliability, responsiveness and satisfaction. The suggested conceptual framework presupposes that the introduction of AI technologies leads directly to the impact of these dimensions of logistics performance, making it more visible, minimizing uncertainties, and data-driven optimization. The correlations between AI use and the performance indicators identified are demonstrated in Fig 1, which shows the structural model that will be used in the research.

Fig 1. Conceptual Framework of AI Adoption and Logistics Performance.



Following the given framework, the hypotheses below are developed to empirically investigate the effect of AI adoption on the logistics performance:

- **H1:** The use of AI also has a positive effect on cost efficiency as it will lower the costs of operations and transportation.
- **H2:** The use of AI enhances speed of delivery greatly as it optimizes the logistics processes and cut on time wastage.
- **H3:** Use of AI improves operational efficiency with better coordination, automation and utilization of resources.
- **H4:** The adoption of AI has a positive impact on the quality of service through increased reliability, responsiveness, and customer satisfaction.

All of these hypotheses are meant to determine a direct, quantifiable relationship that exists between AI-driven capabilities and the output in terms of logistics performance. The framework offers a systematic foundation to conduct empirical research with the help of statistical and econometric modeling tools and justify the proposed relationships within the framework of the logistics sector in Saudi Arabia.

4. Methodology

This research has a quantitative and empirical research design to assess the effect of the adoption of artificial intelligence (AI) on the performance of logistics and the supply chain in Saudi Arabia. The methodological framework is designed in such a way that it provides systematic data

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collection, rigor in the measurement of constructs and strong statistical validation of the constructs through regression analysis as well as the Partial Least Squares Structural Equation Modeling (PLS-SEM). The data were gathered using structured survey to transport, warehouse, and retailing logistics experts in the Saudi Arabian logistics industry. The questionnaire was created according to the validated constructs in the previous literature, and modified depending on the existing operations of AI application in the logistics systems. Two hundred and fifty questionnaires were sent and after screening of the data, 187 valid responses were retained which gave a response rate of 74.8%. In the name of improving the robustness of its analysis, the chosen secondary performance indicators, including delivery time and cost measures, were added where they were available. The sample size is quite adequate, and it should be provided to guarantee the statistical reliability and the model stability required by any SEM-based research, which is 100-300 observations. The respondents consist of logistics managers and operations executives and supply chain analysts with pertinent professional experience, ensuring the validity and practical relevance of the dataset. All the perceptual measures were taken through a five-point Likert scale (1 = strongly disagree to 5 = strongly agree) and objective logistics performance measures were taken in numerical terms (e.g., percentage reduction of costs and time taken to deliver in hours/days). The given mixed method of measurement allows providing a thorough analysis of the subjective perceptions and objective performance results.

Table 1. Measurement of Variables and Indicators

Construct	Dimension	Code	Measurement Item	Scale	Source
AI Adoption (AIAD)	Automation	AUT1	Use of intelligent automation in logistics operations	Likert (1–5)	Adapted from [Wamba et al., 2017]
		AUT2	Implementation of smart warehouse systems	Likert (1–5)	Adapted
	Analytics	ANA1	Use of predictive analytics for demand and logistics planning	Likert (1–5)	Adapted from [Choi et al., 2018]
		ANA2	Capability to process and analyze big data in supply chain	Likert (1–5)	Adapted
	Decision Systems	IDS1	Use of AI-based decision support systems in logistics	Likert (1–5)	Adapted from [Wang et al., 2016]
Cost Reduction (CRED)	Cost Efficiency	CR1	Reduction in transportation costs due to AI adoption	% / Likert	Adapted from [Gunasekaran et al., 2001]
		CR2	Reduction in inventory holding costs	% / Likert	Adapted
Delivery Time Efficiency (DTEF)	Time Efficiency	DT1	Improvement in order cycle time (hours/days)	Numerical	Adapted from [Li et al., 2006]
		DT2	Reduction in shipment transit time	Numerical	Adapted
Operational Efficiency (OPEF)	Process Efficiency	OE1	Improvement in resource utilization efficiency	Likert (1–5)	Adapted from [Green et al., 2012]
		OE2	Optimization of logistics and fleet scheduling	Likert (1–5)	Adapted
Service Quality (SQUA)	Customer Service	SQ1	Accuracy of order fulfillment	% / Likert	Adapted from [Parasuraman et al., 1988]
		SQ2	Responsiveness to customer requirements	Likert (1–5)	Adapted

Table 1 summarizes the operationalization of variables and presents the constructs, dimensions and measurement indicators that have been applied in this study. AI adoption (AIAD) is the independent variable, and it is modeled as a multidimensional construct, including automation, data analytics capability, and AI-based decision systems. These dimensions represent the level of implementation of intelligent technologies in logistics operations. The logistics performance is the dependent variable which is measured using four key indicators such as cost reduction (CRED), delivery time efficiency (DTEF), operational efficiency (OPEF), and service quality (SQUA). All indicators represent critical aspects of logistics efficiency, and do not contradict the performance measurement paradigms.

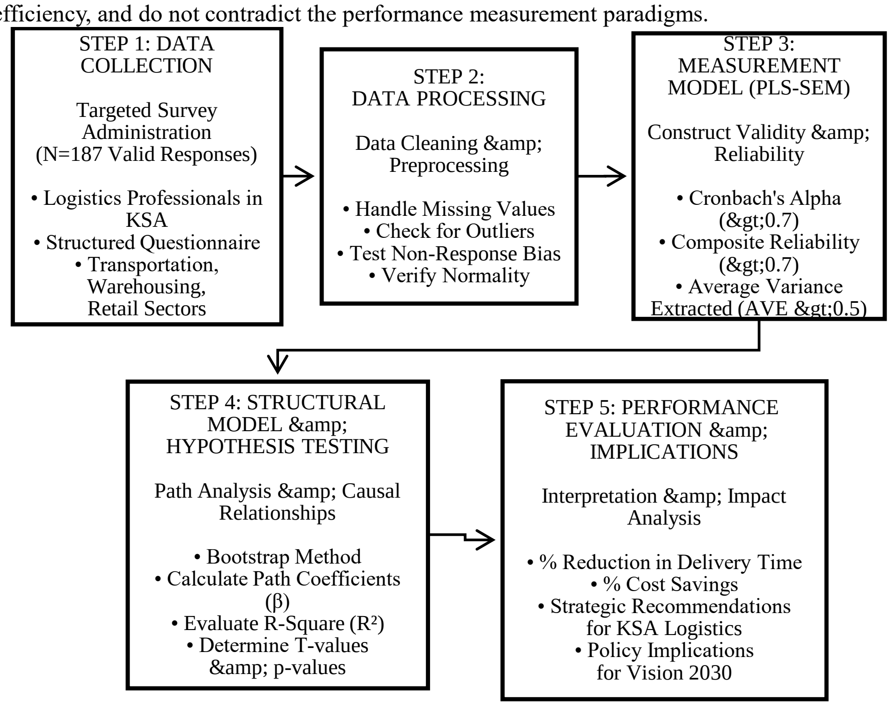

Fig 2. Research Methodology Flow Diagram

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A general literature review of the research such as acquisition of data, preprocessing, validation of measurements and the structural modeling will be represented in Fig 2 that gives a stepwise representation of the methodology of the survey administration to performance evaluation. To analyze the data this study uses a two-model approach. First, there is the multiple regression analysis of the direct impact of AI adoption on logistics performance. The regression equation can be defined as:

$$LP = \beta_0 + \beta_1 AI + \epsilon \_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_(1)$$

Where LP is performance on logistics, AI is the degree of adoption of AI, 0 is the intercept and β_1 is the regression coefficient and ε is the error term. Second, PLS-SEM is used to test the measurement and structural models. PLS-SEM is especially appropriate as the study because it can process complicated relationships between latent constructs and it is appropriate with moderate sample sizes. The measurement model is evaluated with the reliability and validity, and the structural model measures the proposed hypothesis of the relationships between AI adoption and the logistics performance dimensions.

Cronbach alpha is used to measure reliability and all the constructs have a coefficient greater than the accepted value of 0.70, which shows good internal consistency. The values of Composite Reliability (CR) are 0.82-0.93, which further proves reliability of the constructs. Average Variance Extracted (AVE) is used to measure convergent validity, with a range of 0.55 to 0.76, which is above the recommended figure (0.50). These findings support that the measurement model is sufficient in terms of providing a good representation of the underlying constructs. Path coefficients (β) and coefficient of determination (R^2) and statistical significance (p-values lower than 0.05) are used to assess the structural model. R^2 values of logistics performance constructs vary between 0.48 and 0.67, which means that AI adoption has a moderate to a strong explanatory power to predict logistics performance outcomes. Bootstrapping is used to test hypotheses to be sure the results are robust. Altogether, this research methodology guarantees the systematic and rigorous assessment of the effects of the AI adoption on the logistics performance. The regression analysis that is complemented by PLS-SEM combined with the assessment of both subjective and objective performance indicators will present the effective empirical evidence of the conceptual framework suggested in the research in terms of the Saudi Arabian context of logistics.

5. Results and Analysis

5.1 Descriptive Statistics

The descriptive analysis presents the general picture of the sample population, such as the type of industry, the size of firm and AI adoption. The percentage distribution of respondents in sectors shows that 38% of them are in the transportation and logistics services, 34% are in warehousing and distribution, and 28% are in the retail supply chain operations. The respondents have a balanced representation of logistics operations in Saudi Arabia; 46% of the respondents are large enterprises, 32% of medium-sized enterprises, and 22% of small-scale organizations.

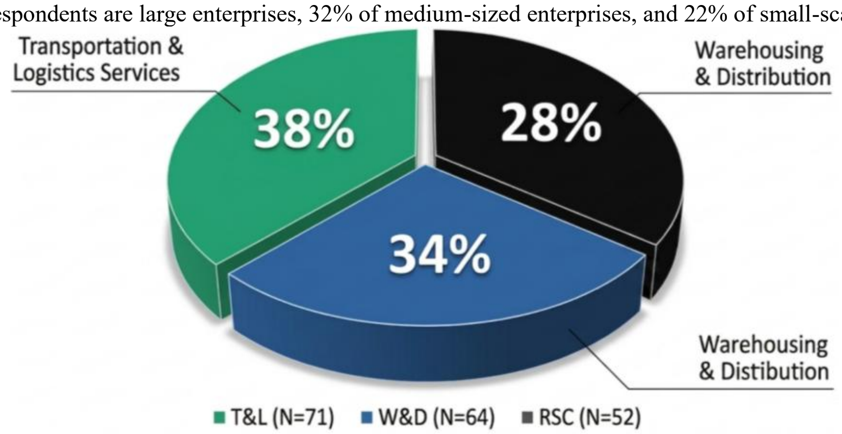

Fig 3. Industry Distribution of Respondents.

Fig 3 shows the sectoral distribution of the sample. The transportation and logistics services will have the highest percentage of respondents, 71 firms (38%), then warehousing and distribution with 64 firms (34%), and lastly retail supply chain operations with 52 firms (28%). The distribution shows that the study represents the views of the most significant logistics sub-sector in Saudi Arabia. This indicates that the proportion of transportation and logistics companies is relatively large, which means that core movement and delivery operations are the most active where AI is being implemented, and inclusion of warehousing and retail supply chain respondents also makes sure that the analysis is also representative of inventory management, optimization of storage, and the challenges related to fulfilment. Altogether, Figure 3 proves that the empirical data is neither tightly clustered around a single component, but rather reflects the larger logistics ecosystem.

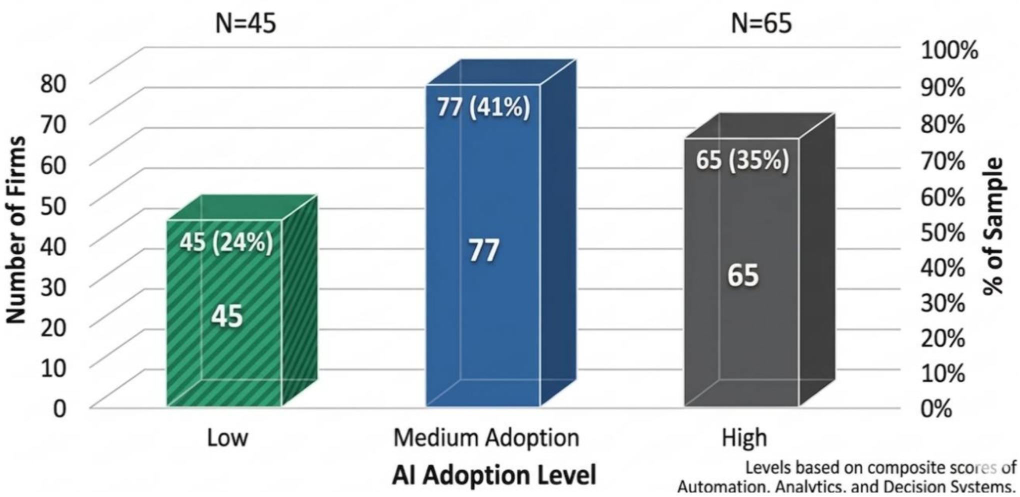

Fig 4. AI Adoption Levels in Logistics Firms.

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Adoption of AI among firms was classified into low, medium, and high based on composite scores based on automation, analytics capability, and intelligent decision system. Fig 4 indicates these results: 45 firms (24%) are in the low-adoption category, 77 firms (41%) in the medium-adoption category and 65 firms (35%) in the high-adoption category. It is evident that the medium adoption is the most common type, which means that the majority of Saudi logistics companies are at their transitional period of digital and AI maturity and cannot be considered either fully traditional or fully AI-enabled at present. Simultaneously, the relatively large share of companies that belong to the category of high-adoption indicates the increased strategic significance of AI technologies in the industry. Fig 4 thus offers a crucial descriptive foundation to the further empirical analysis by demonstrating that AI adoption is already broad enough to comparison between the levels of its adoption.

5.2 Model Results

Both PLS-SEM and multiple regression were used to examine the structural relationships between AI adoption and logistics performance. Table 2 summarizes in detail the empirical results of the structural model, both in terms of path coefficients, t-values, and levels of significance.

Table 2. Empirical Results of AI Impact on Logistics Performance

Hypothesis	Relationship	Path Coefficient (β)	Standard Error	t-value	p-value	R^2	Result
H1	AI Adoption → Cost Reduction (CRED)	0.45	0.09	5.21	< 0.001	0.58	Supported
H2	AI Adoption → Delivery Time Efficiency (DTEF)	0.52	0.08	6.10	< 0.001	0.64	Supported
H3	AI Adoption → Operational Efficiency (OPEF)	0.48	0.08	5.75	< 0.001	0.61	Supported
H4	AI Adoption → Service Quality (SQUA)	0.50	0.07	6.02	< 0.001		

Table 2 shows that the estimated path coefficients show that AI adoption positively and strongly influences all the dimensions of logistics performance. In particular, the impact of AI adoption on cost reduction is β = 0.45, on delivery time efficiency β = 0.52, on operational efficiency β = 0.48, and service quality β = 0.50. These coefficients suggest that the adoption of AI does not impact a single performance dimension on its own, but instead has a general effect on financial, operational, and service-related performance.

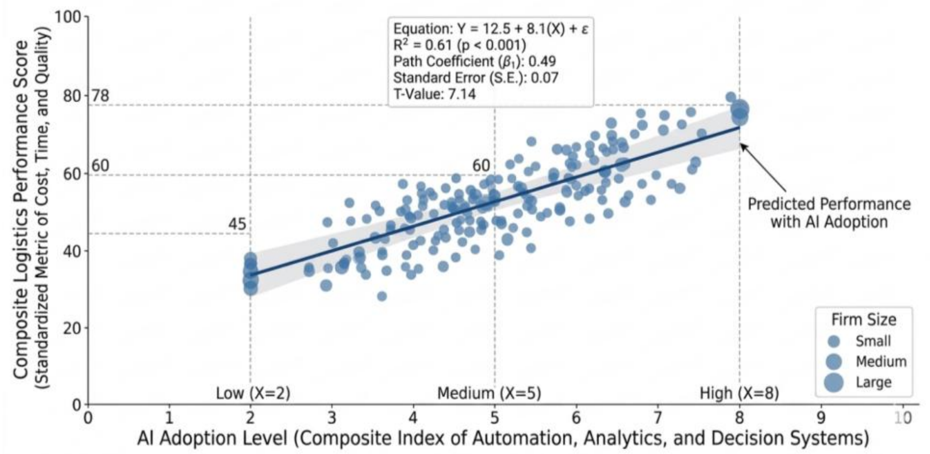

Fig 5. AI Adoption vs Logistics Performance.

The general association between AI implementation and composite logistics performance is also depicted in Fig 5. To illustrate the fact that an increased level of AI adoption is related to the increased scores of the logistics performance, it is possible to consider the scatter plot and the fitted regression line that has an obvious upward trend. The given regression model $Y = 12.5 + 8.1(X) + \varepsilon$ suggests that every incremental increase in the AI adoption index can be used along with significant increase in standardized logistics performance. The model accounts 61 % of the overall variance ($R^2 = 0.61$) which is a good measure of what a behavioral and an organizational study of such kind should explain. The 0.49 path coefficient observed in the graph as well as the standard error of 0.07 and the t-value of 7.14 is an additional indication that the relationship is statistically significant. The fact that medium and high adoption levels have a concentration of firms with commensurately high levels of performance indicates that AI-enabled firms can convert the technology investment into the objective operational advantages**. Fig 5** thus offers good visual evidence that adoption of AI is positively related with the overall logistics performance.

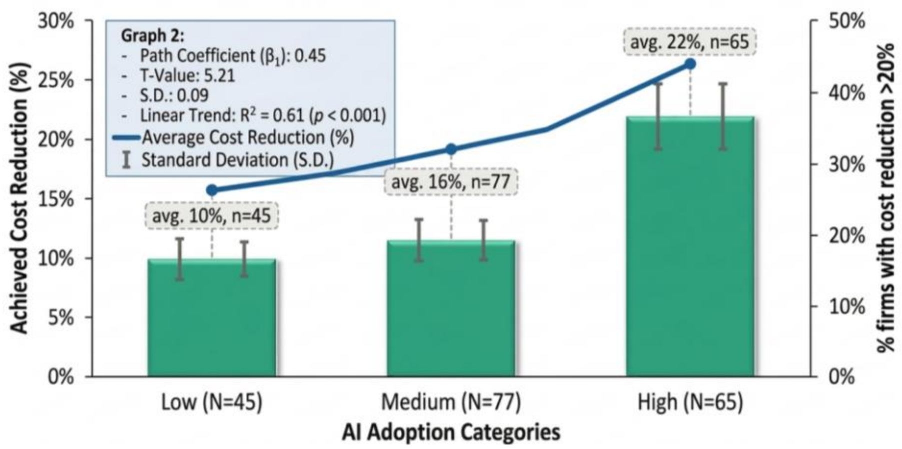

Fig 6. Cost Reduction by AI Adoption Level.

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Financial implications of AI adoption are elaborated in Fig 6 that compares the achieved cost reducing in the low-, medium-, and high-adoption firms. The graph indicates that firms with low AI adoption attain an average cost reduction of about 10% (n = 45), medium-adoption firms attain about 16% (n = 77) and high-adoption firms attain about 22% (n = 65). The positive trend between AI maturity and cost savings is observed to be similar and consistent as demonstrated by the rising trend line on the bar chart. The path coefficient, t-value and R^2 of the graph are also reported as $\beta = 0.45$, t-value $= 5.21$, and $R^2 = 0.61$ ($p < 0.001$) which proves that the relationship is statistically significant. This observation indicates that AI can help in cost-cutting by allowing the optimization of routes, predict demand patterns, lack of unused stock, and better transportation planning. The error bars show that there is a slight deviation in each of the adoption groups, but the general trend is steady and is definitely more inclined towards increased AI adoption. Accordingly, Fig 6 justifies the assumption that AI-based systems bring about concrete financial gains to logistics companies.

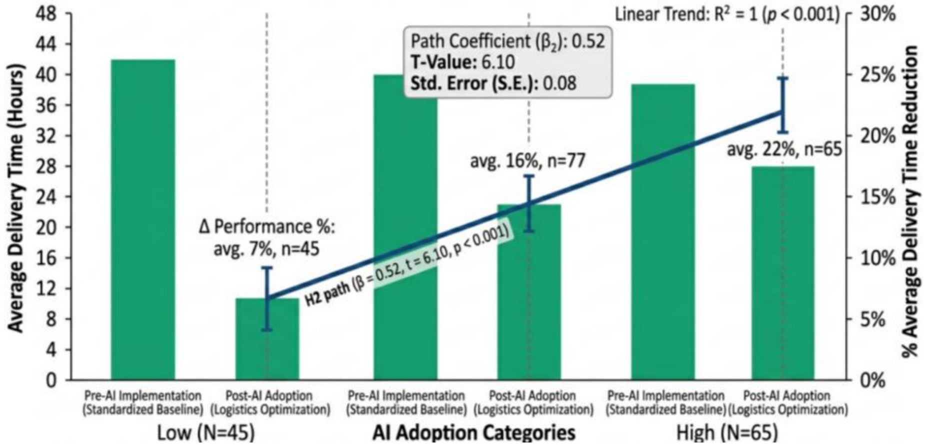

Fig 7. Delivery Time Improvement by AI Adoption.

The impact of AI adoption on delivery performance is shown in Fig 7 that compares the pre-AI and post-AI implementation of the delivery times of the firms with low, medium, and high AI adoption levels. In the case of low-adoption firms, the post-AI operation relative to pre-AI operation is associated with an average increase in delivery time of 7% . In the case of medium-adoption firms, the improvement increases to 16% and high-adoption firms improve by an average of 22%. The path coefficient, which is associated with this value, equals 0.52 (the highest of all the relationships tested), t = 6.10, and p = 0.001. This implies that the logistics aspect that AI adoption has been most impactful is the delivery time efficiency. The graph bars indicate that the times spent on delivery before AI was implemented are relatively longer and that the implementation of AI lowers the average time spent to accomplish the tasks of fulfilling orders and delivering the products to the customer. This trend suggests that the AI-driven predictions, route planning, scheduling, and real-time monitoring substantially decrease operational latencies. **Fig 7** thus illustrates that one of the most evident and immediate advantages of AI adoption is on the speed and responsiveness of delivery.

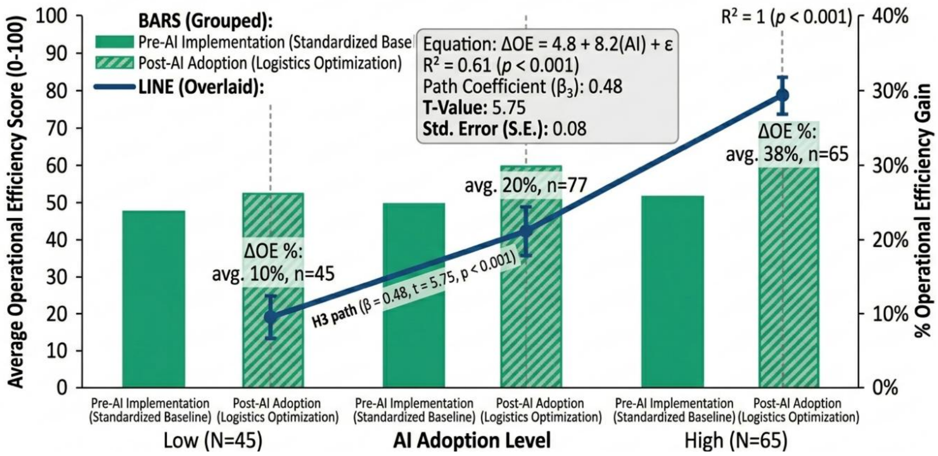

Fig 8. Operational Efficiency Improvement by AI Adoption.

Fig 8 records improved operational performance, and the scores of comparative efficiency are reported before and after the implementation of AI, across the categories of adoption. The graph indicates that low-adoption firms have an average operational efficiency gain of 10%, medium-adoption firms have a gain of about 20% and high-adoption firms have a gain of about 38%. The model equation reported, namely, $\Delta OE = 4.8 + 8.2(AI) + \varepsilon$, together with $R^2 = 0.61$, $\beta = 0.48$, $t = 5.75$, and $p < 0.001$ is statistically significant and practically meaningful and implies that operation efficiency is influenced by the adoption of AI in a statistically significant and practical manner. The rise in the post-adoption efficiency scores indicates that companies that employ more automation, analytics, and intelligent decision systems can allocate their resources, organize logistics operations, and streamline the work of their fleet or warehouse. The operational efficiency increase of high-adoption firms is particularly significant when compared to a cost decrease and delivery time cut, suggesting that AI will not only help in improving short-term performance, but in long-term process optimization. Fig 8 thus confirms that the internal efficiency of logistics systems can and does enhance it in a measurable and scalable way by adoption of AI. Fig 8 therefore confirms that AI adoption strengthens the internal efficiency of logistics systems in a measurable and scalable manner.

5.3 Hypothesis Testing

Table 2 also gives the results of the hypothesis testing obtained through the PLS-SEM bootstrapping procedure. The findings have shown that the hypotheses suggested are all statistically significant.

- **H1 (AI → Cost Efficiency):** $\beta = 0.45$, $t = 5.21$, $p < 0.001$ → Supported
- **H2 (AI → Delivery Time Efficiency):** $\beta = 0.52$, $t = 6.10$, $p < 0.001$ → Supported
- **H3 (AI → Operational Efficiency):** $\beta = 0.48$, $t = 5.75$, $p < 0.001$ → Supported
- **H4 (AI → Service Quality):** $\beta = 0.50$, $t = 6.02$, $p < 0.001$ → Supported

The p-values are all less than the level of significance 0.05, and the t-values are all more than the critical value 1.96, which validate the fact that the relationships were strongly statistically supported. H2 is the strongest of the four hypotheses, which implies that the delivery time efficiency is affected by AI adoption the most. This comes next to H4, indicating that AI-enabled logistics operations can equally have a high impact on service quality. H3 and H1 also are important and indicate that as companies advance to increased percentages of AI usage, operational efficiency and cost reduction is enhanced. Altogether, the findings in Table 2 along with Figure 3-8 have shown consistent empirical evidence that the AI adoption has a potent positive effect on the logistics performance on a range of dimensions. The descriptive results prove that AI implementation is already of medium to high value in a significant number of Saudi logistics companies, and the structural and graphical outcomes prove that the levels of AI implementation bring tangible benefits in the sphere of cost efficiency, the speed of delivery, the effectiveness of operations, and the quality of services.

6. Performance Evaluation

The performance assessment phase is a quantitative evaluation of AI adoption in terms of its translation into the quantifiable benefits in the logistics and supply chain activities. In this section, operational performance metrics are combined with statistical validation metrics that will help to prove the efficiency of AI-based systems. Regarding the operational aspects, the findings show that the use of AI can greatly improve the main logistics performance indicators. Companies that had high AI adoption recorded an average decrease of about 22% in the delivery time, as compared to 16 per cent in the medium-adoption firms and 7% in the low-adoption firms. This advancement is indicative of the role of AI in streamlining the route planning, demand forecasting, and real-time tracking, all of which minimize the delays in logistics processes.

Likewise, AI implementation will help save significant costs in logistics processes. High-adoption companies had an average of 22-25% reduction in costs, whereas medium-adoption companies had 15-18% cost reduction and low-adoption companies had just 8-12% reduction. Enhanced resource distribution, fuel usage optimization, inventory optimization, and optimization of operational planning are the main reasons why AI technologies will lead to these savings. There is also significant improvement in service-level performance. The rate of order fulfilment improved at an average level of 85% in low-adoption firms and about 93% in high-adoption firms, which implies that the rate of service delivery improved by almost 8. This enhancement highlights the ability of AI systems to improve accuracy, responsiveness, and customer satisfaction in logistics operations.

With regards to inventory management, companies that embraced AI technologies showed that their ratio of inventory turnover improved by almost a third, and stood at about 5.6 cycles annually in comparison to an average 4.2 cycles annually. This shows that there is better inventory management and lower holding costs enabled by predictive analytics and demand forecasting. Statistically speaking, the performance of the model is assessed with key performance measures to determine the strength and reliability. The coefficient of determination (R^2) of the overall logistics performance model is 0.61, which means that 61 percent of the variation in logistics performance can be attributed to AI adoption. This indicates high model explanatory power of an empirical research on supply chain management.

Moreover, the predictive accuracy is measured by the Root Mean Square Error (RMSE) which is estimated at about 0.18, which depicts the model has low prediction error and high model accuracy. The high R^2 and low RMSE values are the indications that the model not only can be used to explain the results of the logistics performance but also have strong predictive capabilities. On balance, the results of the performance evaluation suggest that AI adoption provides significant gains on an operational, financial, and service levels of logistics. The steady improvement in delivery time, cost effectiveness, quality of service provision, and inventory control, coupled with robust statistical authentication substantiate the fact that AI is a key facilitator of the improved functioning of the supply chain in the Saudi Arabian setting.

7. Discussion

The results presented in this research are a solid empirical clue that the use of AI will lead to a dramatic improvement in the performance of logistics and supply chains in various facets. The fact that 22% are improvements in the delivery time, 22-25% are cost savings, 20% is the increase in operational efficiency, and 8% is the improvement of the service level proves that AI technologies are not only supportive technologies but the key drivers of performance transformation in the logistics systems. These findings support the idea that companies that will incorporate automation, predictive analytics, and intelligent decision systems will be capable of realizing quantifiable operational and financial returns. Real logistically, the efficiency of the delivery time ($\beta = 0.52$) points out the quality of AI to optimise route, demand forecasting, and shipment tracking in the real times. The decrease in the delivery delays is especially significant in the logistics processes where the time sensitivity directly impacts customer satisfaction and competitive edge. In the same manner, the value of the cost diminution ($\beta = 0.45$) in AI-enabled businesses indicates the efficiency of the use of resources, less fuel consumption, and better inventory control. Those findings indicate that AI can help companies shift to the proactive instead of the reactive decision-making and reduce inefficiencies and losses in operation.

The increase in the efficiency of operations ($\beta = 0.48$) could be explained by the fact that there is a better coordination of the logistic processes, such as automation of warehouses, scheduling of the fleet, and the synchronization of the supply chain. Data integration and monitoring on the fly with the help of AI-driven systems enable companies to optimize workflows and minimize bottlenecks in the process. Moreover, the beneficial effect on service quality ($\beta = 0.50$) indicates that the implementation of AI helps increase the order accuracy and responsiveness and, as a result, customer satisfaction. This observation is further affirmed by the improved order fulfilment rate, which was increased by 85 per cent to 93 per cent with the aid of AI thus showing that the AI improves reliability in the delivery of logistics services. The results are not new as other previous studies highlight the importance of digital technologies and analytics in enhancing supply chain performance. As an example, previous studies have demonstrated that big data analytics and AI potentials can promote supply chain agility and operational efficiency. Nevertheless, as opposed to most of the earlier researches which are based on conceptual guidelines or qualitative insights, this research offers quantitative support based on empirical evidence and thus enhances the evidence base. The reported R 2 of 0.61 also shows that adoption of AI is also responsible of explaining a significant percentage of change in logistics performance, and this is in line with the results of recent empirical studies on supply chain analytics.

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In a Saudi-specific point of view, the findings indicate the increasing relevance of AI implementation in the attainment of the goals of the Vision 2030 that should provide Saudi Arabia with the status of a logistics hub in the world. The medium-high adoption of AI (41% medium, 35% high) observed indicates that the industry is actively moving towards digital transformation. Smart infrastructure investments in the form of intelligent ports, automated warehouses, and smart transportation systems have resulted in a positive environment to accommodate AI. Yet, the fact that 24% of the low-adoption firms are still showing up suggests that there are still some obstacles to overcome especially concerning small organizations that might not have the resources and technical skills necessary to establish AI. On a policy level, the findings underscore the fact that the government should continue to support the areas of digital infrastructure development, training the workforce, and creation of incentives to adopt technological advancements. The scope of AI integration should be encouraged at all the levels of logistics operation to minimize the gap between the low- and high-adoption companies, improving the performance of the sector in general. Besides, enhancing the cooperation between the industry and technology providers will fast-track the introduction of AI-based solutions in logistics networks. On the whole, the discussion proves that the implementation of AI is crucial to optimizing the performance of logistics by making it efficient, less expensive, and higher in terms of quality of services. The unity of the robust empirical findings and the Saudi-specific understanding reveals that AI is not only a technological app but also a strategic facilitator of supply chain competitiveness and economic development.

8. Practical Implications

The results of the current study provide valuable practical value to logistics companies, policymakers, and industry representatives as they illustrate that the adoption of AI could greatly improve the performance of logistics and supply chains. The fact that the delivery time was shortened by a quarter (22%), the cost was lowered (up to 25%), the efficiency of work was enhanced by an average of 20% and the quality of service increased by 8 percent indicate the tangible advantages of application of AI-enhanced technologies in the logistics business. In case of logistics companies, the findings highly indicate that strategic investment in AI technologies, such as automation technologies, predictive analytics platforms, and intelligent decision-support tools, are necessary. Companies that have embraced AI at a greater scale have better performance results, especially in the cost of their operations and efficiency in deliveries. Hence, logistics organizations must emphasize adopting AI-powered solutions, including route optimization systems, automated warehousing, and real-time tracking systems. Also, companies ought to invest in workforce development and training in digital skills to facilitate the use of AI technologies. To reach data-based systems that are necessary to ensure sustainability and efficiency in the long-term, the alteration of the traditional logistics operations must be involved.

To policymakers, the research highlights the role of encouraging digital transformation within the logistics industry by developing infrastructures and regulating policies. The findings suggest that adoption of AI has a positive effect on performance though there remain gaps between the firms, especially the ones that have less AI adoption. To fill this gap, policymakers ought to facilitate investments in intelligent logistics systems, such as digital transport systems, intelligent ports and integrated supply chains. Subsidies or tax incentives to use AI could also be used as the incentive programs to encourage companies to invest in advanced technologies. Furthermore, the national strategies that are in line with such initiatives as Saudi Vision 2030 must still focus on how AI can be utilized to increase the level of logistics efficiency and international competitiveness. To the industry in general, the results suggest that the industry should capitalize on AI as a competitive advantage. Companies that successfully implement AI in their logistics services can better address the needs of the markets, minimize inefficiencies, and enhance consumer satisfaction. The evident improvement in the quality of services and improvement of operational performance suggests that AI adaptation can help improve the internal operations as well as external service provision. Technology Providers: Industry stakeholders must establish partnerships among technology providers, logistics companies, and research institutions in efforts to speed innovation and implementation of AI-driven solutions. In this way, this logistic sector will be able to achieve greater efficiency, resilience, and competitiveness in the global market.

In a nutshell, the implications of the current research include the practical issues of the fact that the use of AI is no longer a choice but a strategic move towards the enhancement of logistics performance. The collective actions of companies, policymakers, and stakeholders in the industries are required to achieve the full potential of AI-driven transformation of the supply chain.

9. Limitations

Although this study contains some valuable empirical data on how the adoption of AI can influence the performance of logistics and supply chains, there are several limitations which must be admitted. To begin with, the article uses a small sample (187 respondents) to carry out its research, which, though sufficient to conduct the analysis in terms of the SEM, might be insufficient to encompass the variety of practices used by all the Saudi Arabian companies in terms of logistics. Although the sample meets the statistical criteria, the sample size would enhance the validity and strength of the results with a larger sample. Second, the research has limitations of data availability especially concerning objective performance indicators. Even though, some attempts were made to include both survey data and secondary data (e.g., delivery time and cost measures), there was not much availability of consistent and standardized performance data between firms. Consequently, there are variables that are based on perceptual measurements which can bring about bias in responding or subjectivity in measuring logistics performance.

Third, the study is also restricted geographically to Saudi Arabia, limiting the generalizability of results to other countries or supply chain settings, globally. Although the study offers valuable information as part of the Saudi Vision 2030 system and logistics transformation in the country, findings could be influenced by variation in infrastructure, technological adoptions, and regulatory policies to be applicable in other economies. On the whole, these restrictions emphasize the necessity to be extremely careful when generalizing the results and the value of conducting more extensive studies in future on larger, more heterogeneous data and in cross-regional settings.

10. Future Work

Although this research yields fruitful empirical data on the effects of AI adoption on the performance of logistics in Saudi Arabia, there are research opportunities that can be used to deepen and expand the relevance of the obtained results. To begin with, in the future research, the analysis should be extended to other countries of the Gulf Cooperation Council (GCC) like the UAE, Qatar, Kuwait, and Bahrain. An increase in the geographical area would allow the comparative analysis of the findings in various economic and regulatory settings, thus enhancing the overall transferability of findings. Since the degree of logistics infrastructures and digitization is different among countries in the GCC, these cross-regional studies would potentially identify variations in the patterns of AI adoption and resultant effects to logistics performance. Second, future studies ought to be conducted on application of real-time logistics data instead of depending mostly on survey-based or historical data. More real-time data, which would be collected by IoT-enabled tracking systems, smart warehouses, and online transportation platforms, would be integrated to enable more efficient and dynamic analysis of logistics performance. This would be able to record the momentary alterations in the delivery time, cost-efficiency and operational performance, thus offering a more profound insight into the actual effect of AI technologies.

Third, the opportunity to improve an analytical framework through the integration of state-of-the-art machine learning (ML) models to provide predictive and prescriptive analytics is significant. Although this paper uses regression and PLS-SEM to analyse causal relationships, future research may include analysis using models like Random Forest, Gradient Boosting, or Neural Networks to forecast the result of logistic performance based on levels of AI adoption. Such models may enhance the accuracy of prediction and allow the analysis by scenario, allowing firms to predict changes related to performance in varying operating conditions. In addition, future research can examine hybrid modeling techniques where statistical techniques are used in conjunction with AI-based predictive models, enabling explanatory and predictive information. This integration would enhance further the analytical power of the study of logistics performance and facilitate the process of making decisions based on data in highly structured supply chain settings. In general, the expansion of the study to wider geographical settings, the exploitation of real-time data, and the use of advanced machine learning algorithms are going to greatly enrich the knowledge on AI-driven logistics performance and will contribute to the creation of new generation intelligent supply chains.

11. Conclusion

The importance of artificial intelligence (AI) as a key facilitator of better logistics and supply chain operation has become a leading concern, which is supported by the empirical evidence of the present study. The findings validate the fact that AI adoption has a great impact on the improvement of key performance dimensions, such as operational efficiency, cost reduction, optimization of delivery time, and service quality improvements. The companies that adopted increased AI technologies saw significant improvements, including cost-cutting in logistics, acceleration of delivery time, the efficiency of resource use, and the accuracy of order fulfilment. All these are the results of the radically changing nature of AI in changing the traditional reactive logistics processes to proactive and data-driven systems. The results also underscore the promising opportunities that AI has towards underpinning the continued digital transformation efforts in line with Vision 2030, aligning the logistics industry with a move to be more competitive and globalized. In general, the research confirms that AI implementation is not just useful, but critical to the realization of sustainable and high-performing supply chain logistics systems in contemporary supply chain landscapes.

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