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The Impact of Artificial Intelligence in Supply Chain Management on Logistics Efficiency in Saudi Arabia

أثر الذكاء الاصطناعي في إدارة سلسلة التوريد على الكفاءة اللوجستية في المملكة العربية السعودية

Dr.Raed Abu Alkhair

رائد أبو الخير

Washington Center: Washington, District of Columbia, US

https://orcid.org/0009-0000-3674-8932

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Abstract:

Saudi Vision 2030 considers the logistics industry an important strategic goal in diversifying the country's economy and the National Industrial Development and Logistics Program aims to connect the national economy to international trade via advanced digitized supply chain networks. In order to achieve this transformation, artificial intelligence is identified as a key technology to improve the industry, with several technologies in its toolkit, like machine learning, demand forecasting, Internet of Things, and machine vision and object detection for inventory management.

Despite the abundance of empirical studies on artificial intelligence in different sectors, like the telecommunications, pharmaceuticals, and manufacturing industries in Saudi Arabia, there is very little quantitative analysis on the impact of artificial intelligence in Saudi Arabia's logistics sector. Furthermore, the quantitative results presented in the few relevant studies are not generalized enough and are insufficiently represented in the national logistics industry.

This paper presents a meta-synthesis approach in order to answer the question: which artificial intelligence technologies are being utilized within the supply chains of Saudi Arabia and what is their impact on the logistics efficiency measures of cost, speed, accuracy, and resilience? The paper reviews 40 articles and uses 30 articles in the meta-synthesis. This meta-synthesis is presented qualitatively because there are no empirical evidence to present a meta-analysis in quantitative format in Saudi logistics industry.

The meta-synthesis finds that technical, organizational, economic, and social barriers that need to be addressed in order to successfully implement artificial intelligence in Saudi Arabia's logistics sector. Furthermore, the meta-synthesis reveals that efficiency measures are not well-defined and standardized, preventing comparison in the meta-synthesis. These findings highlight the need to establish standardized measurement benchmarks for artificial intelligence in logistics. The paper concludes by proposing a research agenda that could support decision-making and strategic planning for government and private sector logistics, policy-makers interested in the national adoption of artificial intelligence in Saudi Arabia, and academics interested in this new research field in Saudi Arabia.

Keywords: Artificial Intelligence; Supply Chain Management; Logistics Efficiency; Saudi Vision 2030; Demand Forecasting; Digital Transformation.

الملخص:

تضع رؤية المملكة العربية السعودية 2030 قطاع الخدمات اللوجستية كركيزة استراتيجية للتنويع الاقتصادي. ويستهدف برنامج تطوير الصناعة الوطنية والخدمات اللوجستية دمج الاقتصاد الوطني في شبكات التجارة العالمية من خلال نشر بنية تحتية رقمية متطورة لسلاسل التوريد.

وقد برز الذكاء الاصطناعي كأداة تمكين محورية لهذا التحول الهيكلي، مع تطبيقات تشغيلية تشمل التنبؤ بالطلب القائم على التعلم الآلي، وأنظمة التتبع المعتمدة على إنترنت الأشياء، وتقنيات تحليل الصور لضبط المخزون. ومع ذلك، لا تزال الأدبيات البحثية المتعلقة بتبني الذكاء الاصطناعي في الخدمات اللوجستية السعودية مجزأة تجريبياً عبر قطاعات معزولة، تشمل الاتصالات والصناعات الدوائية والتصنيع، مع محدودية في التوليف الشامل للنتائج القابلة للقياس عبر القطاعات.

وحيثما تتوفر مؤشرات كمية، فإنها تظل ضيقة النطاق وغير كافية للتعميم على مستوى منظومة الخدمات اللوجستية الوطنية. وتُجري هذه الدراسة تحليلاً توليفياً منهجياً للأدبيات المحكمة، حيث تم تصفية استخراج أولي لأربعين مصدراً للوصول إلى مجموعة منتقاة تضم ثلاثين دراسة عالية التأثير، لفحص تقنيات الذكاء الاصطناعي المطبقة داخل سلاسل التوريد السعودية.

ويُقيّم التوليف تأثيراتها القابلة للقياس على أبعاد كفاءة الخدمات اللوجستية، وتحديداً التكلفة والسرعة والدقة والمرونة، إضافة إلى العقبات البنيوية التي تحد من التوسع في التطبيق. تشير النتائج إلى تكرار العقبات التقنية والتنظيمية والاقتصادية والرقابية بشكل منهجي عبر القطاعات، بينما يتم قياس مكاسب الكفاءة بشكل غير متسق ونادراً ما تتم مقارنتها بمعايير أداء موحدة.

وتخلص الدراسة إلى أن هذا التشتت التجريبي يمثل فجوة جوهرية بين الطموح الاستراتيجي على المستوى الكلي والنتائج التشغيلية القابلة للتحقق. كما تقدم الدراسة دلالات استراتيجية لصانعي القرار الباحثين عن مقاييس أداء موحدة، ولمشغلي الخدمات اللوجستية القائمين بتقييم أولويات الاستثمار التكنولوجي، وللباحثين الأكاديميين الذين يحتاجون إلى خط أساس وطني موحد للبحث التجريبي المستقبلي.

الكلمات المفتاحية : الذكاء الاصطناعي، إدارة سلاسل التوريد، كفاءة الخدمات اللوجستية، رؤية السعودية 2030، التنبؤ بالطلب، التحول الرقمي.

1. Introduction

1.1 Background of the Study

The use of digital technologies has substantially restructured the global supply chain, notably by enabling artificial intelligence (AI) to improve forecasting, routing and inventory management (Richey et al., 2023). By employing complex analytical models, supply chains have shifted from simply monitoring activities to utilizing predictive algorithms that automate key processes and thereby change the way materials and information are transported internationally (Samuels, 2025).

Richey et al. (2023) develop a framework for AI in supply chain research and assert that this technology could significantly reconfigure logistical activities, although only minimal empirical studies have been conducted compared to numerous papers that are theoretical or conceptual in nature. Similarly, Toorajipour et al. (2021) review studies pertaining to the utilization of AI in supply chain management and find that it covers different sub-technologies such as machine learning, natural language processing and robotics, with very little empirical data in relation to the aforementioned literature and most of it from North America and Europe. Research also notes that global supply chain automation improves competitive advantage and decreases mistakes (Ferreira & Reis, 2023), which are dependent on factors such as infrastructure and regulations in different countries (Eyo-Udo, 2024).

Saudi Arabia is a country within the Gulf region that focuses specifically on supply chain technology. Saudi Arabia, through its National Industrial Development and Logistics Program (NIDLP), part of Vision 2030, aims to transform the Kingdom into a leading international logistics hub linking three continents .Within the ambit of this framework, digitizing supply chain processes represents a primary operational need.

Saudi studies reflect this emphasis on digitalization. AI in the cold chain and inventory management in Saudi Arabia's pharmaceutical sector has been noted as part of the efforts under Vision 2030 (Junnaidi & Bhalla, 2024). AlSubaie (2025) examines the use of AI in Saudi Telecom Company's logistics project management, noting the specific use of smart camera systems and image-based analytics to automate monitoring. In addition, Alattas (2024) reports the use of a Technology Adoption Index as a quantitative indicator to assess technology utilization, reporting a moderate average score of 0.58 as well as statistically significant relationships between electronic tracking system usage and ROA.

International studies present general typologies of how AI technology could be used (Kashem et al., 2023; Mohammed et al., 2025), while Saudi studies provide detailed, industry-focused applications of the technology (AlSubaie, 2025; Alattas, 2024; Junnaidi & Bhalla, 2024). There is no literature that has consolidated various industry-based accounts of the use of AI to provide a comprehensive analysis of supply chain AI applications on logistical performance in the country. Thus, although Vision 2030 is a national plan to enhance the global logistics capacity of the Kingdom, the actual impact of its AI initiatives on national logistics performance remains unquantified.

1.2 Statement of the Problem

The available literature confirms that there are empirical studies discussing AI implementation in the supply chains of the Kingdom, but these studies cover the problem at a sectoral level (AlSubaie, 2025; Badghish & Soomro, 2024; Junnaidi & Bhalla, 2024), rather than in the logistics sector as such. AlSubaie (2025) focuses on logistics project management in a specific company in the telecommunications sector and describes the problems faced by this industry sector (including hardware limitations, lack of data security and employee flexibility) without providing data on the problems of other sectors. Junnaidi and Bhalla (2024) discuss the cold chain in the pharmaceutical industry. In this sector, cold chain distribution and problems related to the allocation of costs are the problems of the pharmaceutical industry (AlSubaie, 2025). Badghish and Soomro (2024) limit their review to the adoption of AI in small and medium-sized enterprises, with a focus on performance and not in the field of logistics (Junnaidi & Bhalla, 2024). Although there is a link to AI technologies in e-commerce logistics and digital finance (Al-Baity, 2023; Alqahtani & Alqahtani, 2022), which discusses the relationship between these technologies and the role of natural language and machine learning in consumer supply chain applications, this is not related to the implementation of AI in the industrial sector of the logistics field (Alquraish, 2025). This lack of sectoral focus creates a measurement problem rather than an empty spot in the literature.

Only Alattas (2024), in the reviewed studies, uses an adoption measurement index called the Technology Adoption Index. This study measured its index from a single empirical sample, but it was not discussed, replicated or expanded by other studies focusing on the Kingdom of Saudi Arabia. This means that studies in the field of AI and logistics in the Kingdom depend primarily on descriptive and subjective measurements, such as Khalaf (2025) or Yamin et al. (2024), rather than on performance measurements in the logistics field, and even the two studies (Aljohani & Basiouni, 2025; Alharthi et al., 2020) dealing with the relationship between blockchain and artificial intelligence in improving transparency in logistics depend on the theoretical study and qualitative interviews and lack any quantitative economic data on the relationship in question, which means that there is currently no accurate measurement to describe the actual effect that the artificial intelligence has made on improving the efficiency of logistics in the Kingdom, regardless of its great economic potential mentioned in the Saudi 2030 Vision.

The need to link the two fields, or AI and the logistics sector, is not a research gap, but it is a need to link the empirical studies available today to the general effect on logistics, or the lack of a comprehensive measurement framework that measures all these studies to provide a comprehensive and accurate evaluation of the role of AI in the efficiency of logistics at the national level.

1.3 Research Questions

1. What are the specific AI technologies reported to have been adopted in various industries in Saudi Arabia for use in supply chain and logistics?
2. How much do these documented deployments of AI technologies translate into actual logistics efficiencies as represented in terms of cost efficiency, operational speed, and accuracy/error rates?
3. What are the technological, organizational, economic, and regulatory hurdles that exist across various industries, which impede the adoption of AI for logistics efficiency purposes in Saudi Arabia?

1.4 Research Objectives

1. To find and classify the AI technologies being used in supply chain and logistics in Saudi Arabia.
2. To collate and analyze the logistics efficiencies ascribed to AI technologies in this region.
3. To assess the obstacles to implementing AI technologies categorized into technological, organizational, economic, and regulatory aspects.

4. To compare the AI technology adoption practices observed in various industries with the logistics efficiencies that are stated in the Vision 2030 and NIDLP.

1.5 Significance of the Study

In terms of its implications for policy-makers in Saudi Arabia, this study takes scattered sectoral literature regarding AI technology adoption in the logistics sector and synthesizes it into a coherent framework for evaluating the extent to which AI technology implementation is aligned with NIDLP objectives and targets. In addition, for logistics service providers, the integration of existing knowledge on different challenges faced such as infrastructure limitations and labor skills shortages (Alquraish, 2025; Khalaf, 2025) will serve as a benchmark against which to assess implementation risk ahead of investing in new technology. Finally, this study contributes to the literature on the subject matter on the basis of the roadmap gap pointed out by Richey et al., (2023) by presenting an overview of various sectors with the use of geographical boundaries instead of a single-context case study. Specifically, the findings from telecommunications, pharmaceutical industry, manufacturing, and municipal logistics will provide a basis for future primary studies in the Gulf logistics sector (Aljabri, 2024).

1.6 Definition of Operational Terms

Artificial Intelligence (AI) refers to computer systems that can execute a variety of activities like recognizing patterns, making predictions, and making decisions independently, which in the context of supply chains refers to the various technologies such as machine learning, IoT-based sensing, and image analysis as exemplified by the implementations done in Saudi Arabia (AlSubaie, 2025; Khalaf, 2025).

Supply Chain Management (SCM) is the organization of the flow of materials, information, and finance through procurement, production, and distribution, which encompasses demand forecasting, inventory management, and cold-chain processes that are discussed in the literature reviewed (Junnaidi & Bhalla, 2024; Toorajipour et al., 2021).

Logistics Efficiency refers to the assessment of logistics performance and impacts in terms of costs, speed/time, and accuracy and resilience, which for the purpose of the current study is viewed through various metrics such as Technology Adoption Index and Return on Assets coefficients (Alattas, 2024).

2. Research Methodology and Tools

2.1 Research Design

To bring together the empirical evidence from peer-reviewed literature on the use of artificial intelligence in supply chain and logistics in Saudi Arabia, the present study is based on a qualitative systematic review. The meta-synthesis approach has been used because the sources reviewed differ in terms of methodology, discipline, and research outputs. In this case, it is important to employ a synthesis method that will unify qualitative case study results with the minimal quantitative measures available. Since there is no single primary study offering empirical data for a national level assessment, meta-synthesis is the only viable method that can help in overcoming the difficulties related to fragmentation of research results, which makes it impossible to analyze AI effect on Saudi logistics on a broader scale.

2.2 Data Collection and Search Protocol

In terms of the current study, the systematic gathering of the structural data from the research tool named Elicit focused on the peer-reviewed literature published between the years of 2020 and 2025. After the extraction process, forty publications related to the phenomenon of artificial intelligence, supply chain management, and digital transformation from the area of the Gulf and beyond were obtained. The extraction process utilized Boolean operators for linking keywords such as 'Artificial Intelligence', 'Machine Learning', 'Supply Chain Management', 'Logistics Efficiency', and 'Saudi Arabia' to bring about one large body of information. Thus, the produced data base came up with fields related to AI Implementation Contexts, Impact of Logistics Efficiency, Barriers and Enablers of Implementation, AI Technology selected, Methodological approach, and Geographic Focus, thus allowing to compare the data coming from different sources.

2.3 Inclusion and Exclusion Criteria

In order to achieve the highest degree of academic rigor as well as blind applicability of the work to research questions, strict and rigorous inclusion and exclusion criteria were applied to the original forty sources. In order for the sources to qualify for inclusion to the final corpus, they had to meet three conditions cumulatively, which were: to be directly related to the phenomenon of artificial intelligence or closely related digital technologies (such as machine learning, IoT, or blockchain) in the context of supply chain or logistics; to be associated with at least one dimension/severity of logistic efficiency (i.e., cost, speed, accuracy, resilience); and to demonstrate sufficient methodological transparency that permits identifying possible barriers/enablers of their implementation. Studies that were mainly focused on medical diagnostics, healthcare delivery, or humanitarian pedagogy without any mention of logistics application were excluded from the corpus systematically. All of this rigor was needed to narrow down the samples from the originally estimated forty sources to 30 selected studies. Most of the studies selected demonstrate direct applicability to Saudi Arabian sectors, while some of them provide theoretical relevance for studying AI use in supply chain regardless of the country or region (Ferreira & Reis, 2023; Khalifa et al., 2021; Nozari et al., 2022).

2.4 Data Extraction and Synthesis Matrix

Automated column generation methods were employed by the structured data acquisition process to analyze thirty various data sources depending on set analytical categories and provide relevant quotations utilizing the original meaning. The automatic matrix created was followed by the quality check of the information which was analyzed against abstracts and full texts of the sources. When validating the information, the emerging patterns were classified into three synthesis dimensions: technology used, the effect produced, and the impediment type.

3. Theoretical Framework and Literature Review

3.1 Theoretical Framework

Drawing on two theoretical frameworks to analyze AI adoption, the Technology-Organization-Environment (TOE) framework and Resource-based View (RBV), we can see how these concepts provide a lens to study this research. While the Technology-Organization-Environment (TOE) framework attributes adoption outcomes to the influence of the three constructs – technological, organizational, and environmental conditions the RBV emphasizes the role of firm-specific resource endowments on the adoption.

This TOE lens allows the explanation to capture variations in AI adoption across sectors in Saudi Arabia (instead of simply stating an expected national level of AI adoption). Companies in technology-driven and organizationally prepared sectors, like telecommunications (AlSubaie, 2025), are better positioned to adopt AI than companies in environmental constrained sectors like SMEs (Badghish & Soomro, 2024). In Saudi Arabia specifically, the environmental dimension is critical as Vision 2030 policies exert institutional pressure on firms to implement digital technologies (Alquraish, 2025).

RBV, on the other hand, provides a conceptualization of AI adoption as a resource that creates a strategic level of competitive advantage. This means AI as a resource can be considered valuable, rare, and under the right circumstances, it can be impossible to substitute and imitate (Yamin et al., 2024). This implies that a firm's logistics can be transformed to create a competitive advantage from an AI resource. Vision 2030 and the National Industrial Development and Logistics Program (NIDLP) assume this is what will lead to a more competitive logistics system in Saudi Arabia. We, however, assume this to be a matter that requires verification and evidence, since the Resource-based View emphasizes a firm's ability to accumulate resource capabilities and these capabilities can be heterogeneous (rather than uniform) across firms (which then means the assumption of Vision 2030 might not hold true). This study uses TOE to study the reasons for variation in adoption (and RBV to study the ability of AI at a firm-level to achieve the logistics efficiency goals outlined in the policy document).

3.2 Synthesis of Deployed AI Technologies in Saudi Supply Chains

As detailed in Table 1, the empirical literature documents a diverse array of artificial intelligence technologies deployed across various sectors within the Saudi Arabian economy and comparable global contexts.

Table 1: *Matrix of Deployed AI Technologies and Operational Applications in Saudi Industry*

AI Technology Category	Specific Operational Applications	Primary Empirical Sources
Computer Vision / Image Analysis	Smart camera-based container and truck label identification; real-time video analytics for port operations; automated quality inspection	AlSubaie (2025); Ismaeil & Lalla (2024); Muafa et al. (2024)
Machine Learning & Predictive Analytics	Demand forecasting; predictive maintenance; intelligent routing; inventory optimization	Alattas (2024); Alquraish (2025); Belhadi et al. (2021); Cannas et al. (2023); Pan et al. (2024)
Internet of Things (IoT) & Sensors	Real-time tracking; cold-chain condition monitoring; sensor-based decision support; fleet management	Junnaidi & Bhalla (2024); Khalaf (2025); Nozari et al. (2022); Mohammed et al. (2025)
Big Data Analytics	Inventory optimization; demand pattern analysis for SME operations; market fluctuation response	Badghish & Soomro (2024); Kashem et al. (2023); Samuels (2025); Toorajipour et al. (2021)
Drones & Autonomous Systems	Supply chain decision-making support; physical inventory verification; automated warehousing	Alhazmi et al. (2025); Eyo-Udo (2024); Ferreira & Reis (2023)

Blockchain & Smart Infrastructure	Automated smart port operations; decentralized data validation; secure multi-stakeholder coordination	Aljohani & Basiouni (2025); Alharthi et al. (2020); Charles et al. (2023); Al Azmi et al. (2022)
Natural Language Processing (NLP)	AI-based chatbots for customer engagement; automated procurement inquiries; administrative automation	Al-Baity (2023); Alqahtani & Alqahtani (2022); Basri (2020)

Examining the technologies within the study, it appears that organizations are moving away from the traditionally reactive approach to tracking events to more proactive and automated solutions that anticipate problems before they arise. For instance, in Saudi Telecom Company, instead of manually identifying shipping containers through periodic stocktaking, computer vision is utilized to perform automated continuous identification of containers (AlSubaie, 2025). Another case involves the use of image recognition in healthcare logistics management and administrative task management where visual recognition has reduced human effort by detecting objects to identify their type (Muafa et al., 2024; Ismaeil & Lalla, 2024).

In terms of supply chain and operations management, the use of machine learning to predict and optimize supply chain planning and transportation routing in manufacturing and supply chain management, respectively, shifts the process of trend forecasting from a retrospective analysis of past data to proactive and anticipatory predictions that guide procurement and transportation decisions (Alquraish, 2025; Belhadi et al., 2021). Moreover, the application of predictive analytics in JD Logistics, a Chinese e-commerce company, and in Italian manufacturing firms (Pan et al., 2024; Cannas et al., 2023) serves as a benchmark in terms of the performance and the speed of execution that Saudi companies aim to emulate (Alattas, 2024).

The categorization of the technologies by industry rather than by function may be an interesting indicator. It was found that computer vision was only used in Saudi Arabia's telecommunications sector and some hospitals, while IoT and sensors were used to enhance the pharmaceutical cold chain, and for decision making in supply chain management (Junnaidi & Bhalla, 2024; Khalaf, 2025). This could indicate that industries are selecting technologies according to specific industry demands, and not a national technology adoption policy, which is a dimension of the TOE.

Also, the implementation of 5G at the ports in Saudi Arabia to facilitate automated port management and the utilization of blockchain as a secure communication channel for digital records (Aljohani & Basiouni, 2025; Charles et al., 2023) shows that a well-developed ICT and communication technology infrastructure and security protocols are crucial for the success of advanced AI. Therefore, according to the RBV, organizations that have advanced infrastructure, in this case, high-performance networks, are able to build a sustainable supply chain that is difficult to imitate; this can also mean that the availability of this infrastructure is limited to specific sectors and regions. Thus, this is also in line with the TOE framework as a sectoral aspect of the implementation of the advanced ICT technologies. This suggests that the implementation of a national strategy of logistics improvement in line with Vision 2030 (Alattas, 2024) is not necessarily achieved through a standard and uniform technological path, which has resulted in the current situation where small business companies (Badghish & Soomro, 2024) face a significant technological disadvantage in terms of the technologies implemented.

3.3 Evaluation of Logistics Efficiency Impacts

The measured efficiency impacts are typically organized along four primary axes: cost, speed, accuracy, and resilience. AlSubaie (2025) observes that efficiency gains in cost and time occurred at Saudi Telecom Company, but the gains are not measured numerically. Similarly, improvements in inventory management, accurate demand forecasting and lower stock outs have been achieved in the pharmaceutical cold chain (Junnaidi & Bhalla, 2024), but again no quantification is available. Khalaf (2025) shows efficiency improvements in the domains of cost, speed, sustainability and resilience in relation to IoT and data analytics deployment but does not provide numerical evidence. Aljabri (2024), in the domain of municipal logistics and urban planning, points to the optimisation of traffic flow and routes for waste collection to increase speed and sustainability, though evidence is derived through a qualitative review of the literature and is not measured by econometrics.

Only Alattas (2024), in the corpus on Saudi Arabia, presents data that are standardized and measured quantitatively, citing an average Technology Adoption Index of 0.58 in addition to positive coefficients for the impact of electronic tracking system adoption on Return on Assets. However, a single value from an isolated sample does not make Alattas (2024) representative of the national performance in the field of logistics efficiency. Without a benchmark for comparison in the literature, however, it remains the only numerical data point. Quantitative results on the impact of artificial intelligence are more available in the international literature, for instance a 6.71% reduction in total logistics costs and a 28.59% improvement in the speed and efficiency of deliveries for JD Logistics (Pan et al., 2024) or the reduction of transportation costs by 44% as projected by the autonomous transportation strategy of Dubai (Khalifa et al., 2021).

In summary, the above-mentioned methodological heterogeneity is not just a gap but rather a source of vulnerability of the research field. In the field of Saudi Arabia, claims and assertions related to the contribution of artificial intelligence to logistics efficiency are generally based on qualitative analysis, self-reporting or perceived measures (Khalaf, 2025; Yamin et al., 2024; Basri, 2020), and therefore the improvements are neither comparable between studies nor aggregable into sectoral composite, nor verifiable against a common benchmark. This means that while Vision 2030 and the NIDLP set performance objectives on quantitative and temporal measures, one cannot confirm that the documented adoption of artificial intelligence is consistent with the achievement of national logistics goals based solely on the existing evidence in the literature.

3.4 Taxonomy of Structural Implementation Barriers

The empirical evidence synthesized in Table 2 categorizes the recurring structural constraints that impede the scaling of AI technologies across Saudi Arabian supply chains.

Table 2: *Cross-Sector Taxonomy of AI Implementation Barriers in Saudi Arabia*

Barrier Category	Concrete Empirical Evidence from Dataset	Representative Sources
Technical	Hardware infrastructure deficits; cybersecurity vulnerabilities; integration challenges with legacy systems; cold-chain distribution complexity; scalability issues	AlSubaie (2025); Alquraish (2025); Nozari et al. (2022); Samuels (2025)
Organizational	Insufficient employee skills and adaptability; resistance to change; lack of top management support; hospital/corporate bureaucracy	AlSubaie (2025); Khalaf (2025); Muafa et al. (2024); Cannas et al. (2023); Belhadi et al. (2021)
Economic	High initial investment costs; uncertainty regarding return on investment (ROI); cost-allocation deficiencies; maintenance expenses	Alattas (2024); Junnaidi & Bhalla (2024); Aljabri (2024); Khalifa et al. (2021)
Regulatory / Governance	Absence of clear regulation on AI ethics and liability; underdeveloped transparent frameworks; compliance challenges; lack of legal frameworks for smart contracts	Al-Baity (2023); Alharthi et al. (2020); Charles et al. (2023); Al Azmi et al. (2022)
Data-related	Data privacy and security concerns; requirement for high-quality, consistently structured data; data fragmentation and silos; transparency in algorithmic decision-making	Khalaf (2025); Charles et al. (2023); Badghish & Soomro (2024); Kashem et al. (2023); Mohammed et al. (2025)

The fact that the same five categories of barriers are recurring in the telecommunications, pharmaceutical, manufacturing, and general logistics services sectors suggests that these barriers are systemic rather than specific to one industry. Economic and technical barriers are present in virtually every study that had a barrier classification, suggesting that AI adoption relies on the same economic and technical preconditions regardless of which specific task AI is used to automate. The technological and organizational barriers are also present in all studies, suggesting that the technological and organizational conditions in the TOE framework must exist before the environmental condition has any effect.

Technical and data barriers precede benefits to firm efficiency. If an organization has the capital to adopt the technology but not the infrastructure to run the technology (Nozari et al., 2022), it will not achieve full efficiency and its results will not be consistent. If an organization does not have the data infrastructure to enable the technology to work (Kashem et al., 2023), results will be suboptimal and it will never achieve stability. This could mean that a firm is not achieving full efficiency from its technology, or it could mean that the technology is not being utilized at all, depending on the specific nature of the barriers encountered.

The organizational barriers and human capital barriers also hinder the implementation of AI as a resource. If the firm does not have the skills needed to use AI and leadership is resistant (Muafa et al., 2024; Cannas et al., 2023), there will be inefficiency and the firm will be unable to gain the full competitive advantage of using AI, according to the resource-based view.

Regulatory and ethics barriers are the final barriers in the environmental dimension. The lack of unified ethical regulation across the country for AI, which is documented in the financial services and telecommunications sectors (Al-Baity, 2023; AlSubaie, 2025), is a national characteristic and not one that firms can solve on their own. The data standard requirement is also documented by almost all sectors and therefore is also a national characteristic and not a firm one. These barriers are a national level problem and not a business level problem according to the environmental dimension in the TOE framework. This means that national level regulatory conditions are an impediment to achieving the macro-level national logistics performance goals that are a part of Vision 2030.

4. Results

Table 3 delineates the observed empirical patterns regarding how AI implementation affects specific dimensions of logistics efficiency across various Saudi Arabian sectors.

Table 3: *Cross-Sector Evaluation of AI Logistics Efficiency Dimensions*

Efficiency Dimension	Observed Empirical Pattern & Operational Mechanisms	Representative Saudi Sources
Cost Efficiency	Reduced costs reported through electronic tracking, automated inventory control, and dynamic route optimization. Cost savings are frequently cited but rarely quantified, with the exception of a Technology Adoption Index linking tracking to ROA.	AlSubaie (2025); Alattas (2024); Alhazmi et al. (2025); Pan et al. (2024)
Speed & Timeliness	Operational speed, order processing times, and delivery efficiency improved in telecom, pharmaceutical, and general logistics contexts. Mechanisms include automated visual processing and predictive routing.	Junnaidi & Bhalla (2024); Yamin et al. (2024); Aljohani & Basiouni (2025); Eyo-Udo (2024)
Quality & Accuracy	Improved demand forecasting, inventory management, real-time tracking, and reduced stockouts were repeatedly reported. Precision gains rely on machine learning algorithms replacing manual audits.	Alquraish (2025); Khalaf (2025); Alqahtani & Alqahtani (2022); Ismaeil & Lalla (2024)
Resilience & Agility	AI-supported decision-making, predictive risk modeling, and supply chain agility were associated with stronger continuity under disruption, allowing firms to adapt to market volatility.	Yamin et al. (2024); Al Azmi et al. (2022); Basri (2020); Richey et al. (2023); Toorajipour et al. (2021)

Evidence from the studies collectively confirms that AI use in Saudi Arabian supply chains is related to gains in cost efficiency, speed, accuracy, and resilience, but these effects are presented variably across studies, with no common performance indicators.

AI-driven smart cameras, image recognition, and 5G-empowered analytics resulted in reduced costs, higher speed of operations, and increased efficiency in decision making, according to AlSubaie (2025) in Saudi Telecom Company project supply chain management. The underlying mechanism is the replacement of manual processes with visual recognition, leading to improved speed of operations at the logistics nodes, but no baseline comparison is possible to determine the absolute speed gains reported.

AI, IoT and analytics resulted in enhanced insight into real-time data, improved inventory management and demand forecasting, fewer stockouts and faster delivery time according to Junnaidi and Bhalla (2024) in Saudi Arabia's pharmaceutical supply chain, in which Vision 2030 goals are being prioritised in the healthcare sector. In this instance, speed and accuracy are particularly relevant because the product is perishable, and the relevant mechanism is related to ongoing monitoring of product temperature and forecasting of inventory. However, also similar to AlSubaie (2025), the empirical pattern is a survey of executive perception with no quantitative measures of financial impact from avoided spoilage of pharmaceutical products.

In addition to supply chain management of logistics and manufacturing, IoT, sensors, drones, ML, and DL, and blockchain are used to enhance supply chain efficiency, timeliness, quality and sustainability in AI-enhanced supply chain decision making according to Alquraish (2025) and Khalaf (2025). Blockchain, in turn, is reported to help with issues of trust and transparency, resulting in smoother cash flow (Al Azmi et al., 2022) and more efficient procurement (Alharthi et al., 2020).

AI-assisted social media marketing (AISMM) is also discussed as a supply chain management tool in small business and micro-enterprises where AI is applied to improve demand forecast and inventory management, but with the primary focus on improved social media marketing metrics (Basri, 2020; Alqahtani and Alqahtani, 2022).

The only direct quantification found in these empirical patterns is provided by Alattas (2024), who presents an average value of 0.58 for the Technology Adoption Index and describes a positive correlation between adoption of electronic tracking and monitoring systems with Return on Assets. Yamin et al. (2024) extend the efficiency discussion into speed and resilience, with the authors noting the contribution of AI to quicker response, reduced recovery time from incidents, increased accuracy in decision making and greater business continuity and recovery under disruptive circumstances and presenting 80 percent explained variance for supply chain agility as reported by structural equation model.

Overall, the empirical pattern is fairly consistent in suggesting that AI use is associated with enhanced efficiency in Saudi Arabian supply chains in a variety of supply chain performance metrics but also fairly inconsistent in what the metrics are and the values reported, suggesting that a national estimate of supply chain performance improvement cannot be derived.

5. Discussion of Results

The data strongly suggests that there is a significant long-term disconnect between the macro-strategic goals expressed in Vision 2030 and the reality of AI maturity at a firm level. The Saudi logistics policies implicitly presuppose that digital capability will grow organically throughout all industries to yield a measurable national improvement in efficiency leading to an improved position in global logistics indexes.

However, as the synthesis above shows, the available literature is almost entirely focused on firm-specific case studies. In these reports, each industry employs different technologies, aims at different aspects of supply chains, and uses different indicators to measure success. For this reason, it is currently impossible for the literature on the subject to make a single unified and verifiable conclusion about the national efficiency of the logistics system, as the very same underlying indicator efficiency is being used to describe fundamentally different phenomena measured with different, often unquantitative, approaches.

These technical and data-related challenges deserve particular attention because they arose before it became possible to anticipate a rise in efficiency gains from AI. Poor infrastructure, insufficient data sharing, and data security do not just stall system integration, they diminish system performance. After all, the output of an AI model is contingent on a steady, integrated stream of high-quality data. To be functional at all, predictive and prescriptive use cases ranging from forecasting demand in pharmaceuticals supply chains to identifying delivery routes for a production company all require continuous, integrated, high-quality data inputs.

For the reasons of data privacy, legacy data structures that are siloed off, and other related concerns, these learning loops cannot function dependably, which implies that an AI model cannot be adjusted in a regular manner. As a result, a gap between a technology deployment and an efficiency upgrade that follows is likely to be particularly visible, leading companies to adopt advanced AI capabilities that do not yet provide dependable enhancements in the absence of an interoperable, governed data ecosystem. The reality is that an AI model's algorithm might perform as expected, but that algorithm is no better than the underlying data infrastructure upon which it is built.

The literature shows that sector-specific requirements drive AI adoption rather than national-level designations of "strategic industries." The telecommunications sector, the cold chain for pharmaceuticals, and SMEs all have different technology requirements, compliance needs, and capital budgets. These differences clearly point to an AI adoption strategy that is sectoral rather than national in scope: A telecommunications company that deploys computer vision and other 5G-compatible machine learning systems to inspect rural areas for infrastructure damage operates in a different environment than a small enterprise that cannot afford even a basic data analytics platform. The deployment of AI within Saudi Arabia must necessarily vary by sector; the supply chain will have some segments that are very advanced and others that lag significantly behind.

The combination of industry-specific differences and a delayed start while the industry deals with data silos and legacy structures makes it difficult to draw empirical conclusions about macro-logistics efficiency. The available research is quite solid in its identification of firm-level adoption and sector-level perspectives, but much weaker or silent on system-wide efficiency measurements. So, in the coming years Saudi logistics will focus on data interoperability, regulatory frameworks and skills to create measurable and scalable efficiency gains from AI rather than on the public release of new AI adoption policies.

6. Recommendations

6.1 For Saudi Policymakers and NIDLP Authorities

The focus of policymakers should shift from encouraging the general digital transformation process towards putting into practice some standardized operating models. It is necessary to develop a comprehensive system of national logistics performance architecture that will introduce obligatory common indicators of expenses, speed of performance, and the accuracy of forecasting. In addition, authorities ought to set the corresponding data standards and interoperability specifications for all logistics nodes, ports, and transport networks' operations. In the absence of compulsory data-sharing protocols and algorithmic management, the national logistics system will remain a set of disconnected intelligent systems. The establishment of a centralized system of data exchange will allow for an efficient benchmarking of AI initiatives across industries.

6.2 For Logistics Operators and Supply Chain Managers

It is essential that logistics operators first get their basic houses in order before jumping straight into purchasing artificial intelligence (AI) tools.

Logistics organizations need to invest in their employees first by making sure training is focused on data management, AI-based insights and integration of processes across different supply chain functions. Logistics firms that do not invest in their employees or that encounter employee pushback to adoption will fail to create any meaningful value, as the technology alone will not drive efficiency in the system.

Logistics organizations need to build up their systems and cyber defenses before integrating AI tools. It is also important to upgrade existing systems before using AI to control the supply chain. Capital investments should be driven by infrastructure readiness and not technology, in order to deliver a return of capital rather than just investing in digital transformation.

6.3 For Future Academic and Empirical Research

Therefore, future research must be shifted from single-case and perception surveys to cross-sector quantitative designs with a priority on time-series logistics performance measurements; parallel sectors; econometric designs that test the effect of the specific variable AI adoption, in terms of the number of AI projects implemented, on the dependent variables of cycle time; inventory turnover ratio; and the total cost reduction; and finally the development and validation of quantitative efficiency metrics that can be applied to a uniform sample of Saudi logistics organizations.

Future research can be further directed toward quantitative testing of whether the effect of an AI technology on logistics efficiency varies according to the institutional constraints of regulation, infrastructural and organizational, that apply to the deployment of that technology on its efficiency.

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