Macrothink Institute™

International Journal of Social Science Research
ISSN 2327-5510
2026, Vol. 14, No. 3

Critical Success Factors for Artificial Intelligence Application in Healthcare Supply Chain Management: A TOE-Based Study of Mubadala, UAE

Jawaher Adnan Ali Mohammed Alkhawaja

Faculty of Technology Management and Business

Universiti Tun Hussein Onn Malaysia, Malaysia

Norliana Sarpin (Corresponding author)

Faculty of Technology Management and Business

Universiti Tun Hussein Onn Malaysia, Malaysia

E-mail: norliana@uthm.edu.my

Received: April 3, 2026 Accepted: June 10, 2026 Published: June 28, 2026

doi:10.5296/ijssr.v14i3.23871 URL: https://doi.org/10.5296/ijssr.v14i3.23871

Abstract

Artificial intelligence (AI) has become an important digital capability for improving organisational efficiency, decision-making, and operational performance across different sectors, including healthcare. However, while AI has been widely examined in clinical and general healthcare contexts, limited empirical evidence exists on the critical success factors influencing AI application in healthcare supply chain management (HSCM), particularly in the United Arab Emirates. This study investigates the critical success factors for AI application in HSCM using the Technology–Organisation–Environment (TOE) framework, with specific focus on healthcare organisations in Mubadala, UAE. The study examines the effects of technological, organisational, and environmental factors on AI application and evaluates the influence of AI application on four key HSCM outcomes: demand forecasting, inventory management, logistics optimisation, and risk management. A quantitative research approach was adopted, and data were collected through questionnaires from 323 respondents drawn from managerial, logistics, and technical roles within healthcare supply chain organisations in Mubadala, UAE. The data were analysed using partial least squares structural equation modelling (PLS-SEM). The findings revealed that technological factors had the strongest positive effect on AI application (**$\beta = 0.475$, $p < 0.05$**), followed by environmental factors (**β = 0.312, p < 0.05**) and organisational factors (**β = 0.146, p < 0.05**). Together, these factors explained **61.3%** of the variance in AI application. Furthermore, AI application had significant positive effects on demand forecasting (**β = 0.510, p < 0.05**), risk management (**β = 0.445, p < 0.05**), inventory management (**β = 0.430, p < 0.05**), and logistics optimisation (**β = 0.426, p < 0.05**).The study concludes that technological, organisational, and environmental factors are significant critical success factors for AI application in HSCM, with technological readiness emerging as the strongest predictor. The findings also confirm that AI application improves key healthcare supply chain outcomes by enhancing forecasting accuracy, inventory control, logistics efficiency, and risk management capability. This study contributes to the literature by extending the TOE framework to AI-enabled healthcare supply chain management and by providing empirical evidence from the UAE context. Practically, the study offers insights for healthcare managers, policymakers, and supply chain professionals seeking to strengthen healthcare supply chain performance through effective AI application.

Keywords: artificial intelligence, healthcare supply chain management, critical success factors, TOE framework, demand forecasting, inventory management, logistics optimisation, risk management, Mubadala, UAE

1. Introduction

Artificial intelligence (AI) has become one of the most influential digital technologies shaping organisational transformation in the Fourth Industrial Revolution. Across different sectors, AI is increasingly used to enhance decision-making, improve operational efficiency, reduce costs, automate processes, and strengthen service delivery. Through predictive analytics, machine learning, automated decision-making, pattern recognition, and real-time data processing, AI enables organisations to respond more effectively to complex operational challenges and changing market conditions (Duan et al., 2019; Madancian & Taherdoost, 2023; Pournader et al., 2021). These capabilities are particularly important in supply chain management (SCM), where organisations must coordinate the flow of goods, services, information, and resources across multiple stakeholders (Helo & Hao, 2022; Kumar et al., 2023).

The healthcare sector is one of the major areas where AI adoption is becoming increasingly significant. Healthcare organisations depend heavily on effective supply chain operations to ensure the continuous availability of medicines, medical devices, consumables, equipment, and other essential healthcare products. As a result, Healthcare Supply Chain Management (HSCM) plays a critical role in service quality, patient safety, cost efficiency, and continuity of care (Kwon et al., 2016; Kwon & Kim, 2018). Unlike supply chains in many other industries, healthcare supply chains involve urgent, sensitive, and often life-saving products. Therefore, efficiency, accuracy, visibility, responsiveness, and risk control are especially important in this sector (Handfield, 2018; Bialas et al., 2023).

AI has the potential to address many operational challenges in HSCM. AI-enabled systems can support demand forecasting, inventory planning, procurement decisions, logistics optimisation, route planning, supplier monitoring, and supply chain risk detection. Previous studies indicate that AI and big data analytics can improve supply chain performance by enhancing forecasting accuracy, decision quality, inventory control, and operational responsiveness (Bag et al., 2023; Kumar et al., 2020; Seyedan & Mafakheri, 2020). In healthcare supply chains, these benefits are particularly valuable because demand is often uncertain, medical supplies are time-sensitive, and shortages or delivery delays can directly affect healthcare delivery and patient outcomes (Govindan et al., 2020; Friday et al., 2021).

The relevance of AI in healthcare is also evident in the United Arab Emirates (UAE), where digital transformation has become a strategic priority. The UAE has made significant progress in promoting AI, blockchain, digital health platforms, and other emerging technologies across public and private sectors. National AI strategies and healthcare innovation initiatives demonstrate the country's commitment to using digital technologies to improve healthcare delivery, operational performance, and service quality (Al Badi et al., 2021; Dubai Health Authority, 2018). In this environment, healthcare organisations in Mubadala, UAE, provide an important context for examining how AI can support healthcare supply chain transformation.

AI applications in healthcare are already visible in areas such as predictive risk assessment, clinical decision support, medical imaging, disease detection, wearable health-monitoring devices, and personalised treatment planning. These applications show that AI is increasingly being integrated into clinical, operational, and administrative healthcare processes (Chen & Decary, 2020; Reddy et al., 2019; Sun & Medaglia, 2019). However, while much attention has been given to the clinical use of AI, less attention has been paid to how AI can improve the supply chain systems that support healthcare delivery. This is an important issue because the effectiveness of healthcare services depends not only on clinical expertise, but also on the availability, movement, and management of critical medical resources.

Despite the growing interest in AI, healthcare supply chains continue to face several challenges. These include high operational costs, limited supply chain visibility, fragmented information systems, poor data integration, inventory shortages, stockouts, quality control issues, supplier coordination difficulties, and vulnerability to disruptions. Such challenges may affect the availability of medicines and medical supplies, increase healthcare costs, and weaken the reliability of healthcare service delivery (Bialas et al., 2023; Essila, 2023; Kaupa & Naudé, 2021). In the UAE context, these issues are especially important because healthcare organisations operate in a rapidly developing and technology-driven environment that requires strong coordination, organisational readiness, and effective digital supply chain practices (Hussain et al., 2020; Al Badi et al., 2021).

The need for effective HSCM is becoming more important as healthcare demand continues to increase in the UAE. Growing healthcare needs require supply chains that are efficient, responsive, secure, and resilient. AI offers a potential solution by improving forecasting accuracy, enhancing inventory visibility, supporting logistics coordination, and strengthening risk management capability (Jebbor et al., 2022; Aljohani, 2023). However, the successful application of AI does not depend on technology alone. It also depends on organisational readiness, managerial support, employee capability, financial resources, regulatory conditions, supplier relationships, and external environmental pressures. Therefore, understanding the critical success factors that influence AI application is essential for improving HSCM performance.

This study adopts the Technology–Organisation–Environment (TOE) framework to examine the critical success factors for AI application in healthcare supply chain management. The TOE framework provides a suitable theoretical lens because it explains technology adoption through three major dimensions: technological, organisational, and environmental factors (Tornatzky et al., 1990). In the context of this study, technological factors include digital infrastructure, data availability, system integration, and technical capability. Organisational factors include top management support, employee readiness, financial resources, organisational culture, and digital transformation commitment. Environmental factors include regulatory requirements, supplier relationships, stakeholder expectations, market uncertainty, and external supply chain pressures.

Although AI has been widely studied in general healthcare and broader supply chain contexts, there remains limited empirical evidence on the critical success factors that influence AI application in healthcare supply chain management, particularly in Mubadala, UAE. Previous studies have examined AI in SCM, healthcare supply chain digitalisation, supply chain resilience, and AI adoption challenges (Addy, 2023; Bag et al., 2023; Bialas et al., 2023; Kumar et al., 2023). However, the specific role of technological, organisational, and environmental factors in supporting AI application, and the subsequent influence of AI on HSCM outcomes such as demand forecasting, inventory management, logistics optimisation, and risk management, remains underexplored in this context.

This gap is important because healthcare supply chains are complex, context-specific, and difficult to standardise across different institutional and national settings. Healthcare supply chains involve multiple stakeholders, strict service requirements, patient safety concerns, emergency demand, regulatory obligations, and high levels of uncertainty (Kumar et al., 2023; Friday et al., 2021; Hossain et al., 2022; Ivanov & Dolgui, 2020). Therefore, context-specific empirical research is needed to understand how AI can be effectively applied to improve HSCM performance in the UAE healthcare environment.

Accordingly, this study investigates the critical success factors for AI application in healthcare supply chain management in Mubadala, UAE, using the TOE framework. Specifically, the study examines how technological, organisational, and environmental factors influence AI application, and how AI application affects demand forecasting, inventory management, logistics optimisation, and risk management and mitigation. By addressing this issue, the study contributes to the growing literature on AI-enabled healthcare supply chains and provides practical insights for healthcare managers, policymakers, and supply chain professionals seeking to improve supply chain efficiency, resilience, and decision-making in the UAE healthcare sector.

2. Literature Review

The Fourth Industrial Revolution has significantly transformed the way organisations operate across different sectors. This transformation is mainly driven by the increasing adoption of disruptive digital technologies such as artificial intelligence (AI), blockchain, big data analytics, and the Internet of Things (IoT). These technologies are reshaping organisational processes by improving automation, connectivity, data visibility, operational efficiency, and decision-making capability (Duan et al., 2019; Pournader et al., 2021; Seyedghorban et al., 2020). Among these technologies, AI has received growing attention because of its ability to support learning, reasoning, problem-solving, prediction, and decision-making processes that were traditionally associated with human intelligence (Madancian & Taherdoost, 2023). Baviskar et al. (2023) further noted that AI improves system effectiveness and productivity by enabling machines to perform human-like tasks, especially in complex decision-making environments.

AI has been defined in different but related ways in the literature. McDougall (2019) described AI as a computer-based system capable of observing information, assessing situations, and making decisions. Similarly, Bali et al. (2019) defined AI as computer programs that imitate human cognitive functions, including reasoning, discovering meaning, generalising knowledge, and applying previous experience to achieve specific goals. Sun and Medaglia (2019) explained that AI technologies involve systems that analyse their environment and make decisions that increase the likelihood of achieving predetermined objectives. These definitions show that AI is not simply a technological tool, but a strategic decision-support capability that can improve organisational responsiveness, efficiency, and competitiveness (Duan et al., 2019; Helo & Hao, 2022).

The adoption of AI and other Industry 4.0 technologies is increasingly motivated by the need to improve operational performance, reduce costs, strengthen decision-making, and create competitive advantage. Kumar et al. (2023) identified financial benefits, timely decision-making, and the development of competitive business models as important reasons for adopting transformative technologies such as AI, blockchain, and IoT. These motivations are especially relevant in supply chain management (SCM), where organisations must coordinate complex flows of goods, services, information, and resources across suppliers, manufacturers, distributors, service providers, and customers. As a result, SCM has become one of the major areas in which AI is applied to improve planning, coordination, visibility, and operational performance (Pournader et al., 2021; Helo & Hao, 2022).

AI is transforming how organisations plan, execute, monitor, and optimise supply chain activities. In SCM, AI supports demand forecasting, logistics monitoring, warehouse automation, procurement decisions, distribution optimisation, inventory control, and risk management. Pournader et al. (2021) showed that AI applications in SCM are increasingly used to improve decision-making, process automation, and operational responsiveness. Similarly, Helo and Hao (2022) demonstrated that AI can support operations and supply chain management by improving planning, coordination, and decision quality. AI and big data analytics are also important for managing supply chain uncertainty because they allow organisations to process large volumes of data, detect hidden patterns, and make more accurate predictions than traditional analytical methods (Hazen et al., 2014; Seyedan & Mafakheri, 2020).

The practical benefits of AI in SCM have also been confirmed in empirical and industry-based studies. AI can improve forecasting accuracy, enhance inventory management, reduce operational costs, support efficient logistics decisions, and improve customer service levels. For example, Seyedan and Mafakheri (2020) showed that predictive big data analytics can improve demand forecasting by enabling organisations to analyse complex and dynamic supply chain data. Kumar et al. (2020) also found that AI techniques can strengthen supply chain performance in healthcare by improving forecasting and operational decision-making. In addition, McKinsey and Company (2019) reported that organisations adopting AI-based supply chain systems experienced improvements in logistics costs, inventory levels, and service levels. These findings suggest that AI can generate operational, financial, and strategic benefits across different areas of supply chain management.

The relevance of AI is particularly important in healthcare supply chain management (HSCM), where the timely availability of medicines, drugs, consumables, medical devices, equipment, and other healthcare products is essential for service delivery. HSCM involves the planning, procurement, storage, distribution, and management of healthcare products and services across healthcare organisations and supply chain partners (Kwon et al., 2016). Kwon and Kim (2018) further emphasised that effective supply chain implementation in healthcare is important for improving quality, cost efficiency, and service delivery. Unlike general supply chains, healthcare supply chains operate in a sensitive environment where delays, shortages, poor visibility, and supply failures may directly affect patient safety and continuity of care (Handfield, 2018; Orji, 2020).

AI provides important opportunities for improving HSCM because healthcare supply chains often operate under conditions of uncertainty, urgency, strict service requirements, and demand variability. Addy (2023) noted that AI can support vaccine distribution by improving allocation, transportation logistics, forecasting accuracy, and inventory optimisation in healthcare systems. Similarly, Bag et al. (2023) found that AI and big data analytics can empower healthcare supply chains by improving collaboration, absorptive capacity, and supply chain responsiveness. These capabilities are valuable because healthcare organisations must manage fluctuating demand, emergency requirements, stock availability, supplier reliability, and the timely delivery of critical medical products (Govindan et al., 2020; Friday et al., 2021).

In the context of the United Arab Emirates, the increasing application of AI in healthcare reflects broader national efforts to improve digital transformation, innovation, and service quality. The UAE has made notable progress in promoting AI adoption across healthcare and other sectors. Al Badi et al. (2021) examined AI adoption challenges in UAE healthcare and highlighted the importance of technological, organisational, and institutional conditions in shaping successful AI implementation. Hussain et al. (2020) also showed that healthcare supply chains in the UAE require effective organisational practices to improve performance and operational effectiveness. These studies suggest that AI application in UAE healthcare should be understood not only as a technological issue, but also as a strategic and organisational transformation process.

This study is grounded in the Technology–Organisation–Environment (TOE) framework, which provides a useful theoretical lens for examining the critical success factors influencing AI application in HSCM. The TOE framework explains technology adoption through three main dimensions: technological, organisational, and environmental factors (Tornatzky et al., 1990). Technological factors refer to the internal and external technologies relevant to an organisation, including digital infrastructure, data availability, system integration, technical compatibility, and analytical capability. Organisational factors include top management support, financial resources, employee readiness, organisational culture, staff competence, and commitment to digital transformation. Environmental factors include regulatory pressures, stakeholder expectations, supplier relationships, competitive pressure, market uncertainty, and external supply chain disruptions.

Technological factors are particularly important for AI application because AI systems depend on reliable data, digital infrastructure, technical expertise, and integration with existing supply chain platforms. In HSCM, poor data quality, fragmented systems, weak interoperability, and limited analytical capacity may restrict the successful use of AI. Hazen et al. (2014) emphasised the importance of data quality in analytics-driven supply chain decision-making, while Bag et al. (2023) highlighted the role of AI and big data analytics in strengthening healthcare supply chain responsiveness. Therefore, healthcare organisations with stronger technological readiness are more likely to apply AI effectively in forecasting, inventory control, logistics optimisation, and risk monitoring.

Organisational factors also play a central role in AI application. Even when AI technologies are available, their successful implementation depends on internal organisational readiness. This includes leadership support, employee skills, financial investment, change management, staff acceptance, and strategic alignment with organisational goals. Al Badi et al. (2021) indicated that organisational issues are among the major challenges influencing AI adoption in UAE healthcare. Similarly, Hussain et al. (2020) showed that healthcare supply chain performance is influenced by organisational practices and internal capabilities. These findings suggest that AI application in HSCM requires not only advanced technology, but also strong managerial commitment and human resource readiness.

Environmental factors further influence AI application in healthcare supply chains. Healthcare organisations operate within complex external environments shaped by government regulations, supplier relationships, stakeholder expectations, market uncertainty, emergency demand, and disruption risks. In healthcare, environmental pressures are especially important because organisations must ensure compliance, service continuity, product safety, and timely delivery of critical medical supplies. Studies on supply chain resilience and disruption management show that external uncertainty can encourage organisations to adopt digital technologies to improve visibility, responsiveness, and risk mitigation (Ivanov & Dolgui, 2020; Aljohani, 2023). Therefore, environmental conditions may significantly shape the extent to which healthcare organisations apply AI in supply chain management.

AI applications in healthcare are visible in several areas, including clinical decision support, predictive analytics, medical imaging, administrative automation, disease detection, wearable health-monitoring devices, and personalised treatment planning. Chen and Decary (2020) argued that AI provides important opportunities for healthcare leaders by supporting clinical and operational decision-making. Reddy et al. (2019) also noted that AI-enabled healthcare delivery can improve care processes by supporting diagnosis, decision-making, and service efficiency. In addition, AI has been associated with early disease detection and personalised treatment, which can improve patient outcomes and support more responsive healthcare delivery (Badidi, 2023; Chintala, 2023). These developments show that AI is increasingly being integrated into both clinical and operational dimensions of healthcare.

In HSCM, one of the most important contributions of AI is demand forecasting. Accurate forecasting is essential because shortages of critical medical supplies can disrupt healthcare services, while excess inventory can increase holding costs, waste, and expiration risks. Jebbor et al. (2022) demonstrated that AI-based forecasting models can support hospital asset demand planning, particularly during disasters and emergency conditions. Govindan et al. (2020) also developed a decision-support approach for demand management in healthcare supply chains during epidemic outbreaks, highlighting the importance of predictive tools for managing uncertainty. These studies suggest that AI can improve the ability of healthcare organisations to align supply with actual demand and reduce stockout risks.

AI also contributes to inventory management in healthcare supply chains. Effective inventory management is necessary to ensure that essential medicines, consumables, and medical equipment are available when needed. AI-enabled systems can support real-time inventory visibility, automatic replenishment decisions, demand-based stock planning, and reduction of overstocking or understocking. Friday et al. (2021) emphasised the importance of collaborative inventory capabilities in mitigating stockout risks during health emergencies. Similarly, Kumar et al. (2020) suggested that AI techniques can enhance healthcare supply chain performance by supporting better forecasting and inventory-related decisions. These findings indicate that AI can strengthen inventory efficiency and improve the reliability of healthcare supply operations.

AI further supports logistics optimisation in HSCM. Healthcare logistics involves transportation planning, delivery scheduling, route optimisation, distribution coordination, and the movement of time-sensitive medical products. AI can analyse logistics data, identify efficient routes, optimise delivery schedules, and improve resource allocation. Soumpenioti and Panagopoulos (2023) showed that AI can support medical logistics by improving distribution network optimisation, reducing transportation costs, and shortening delivery times. Trappey et al. (2018) and Luong et al. (2020) also indicated that digital technologies such as AI and IoT can improve logistics coordination, tracking, and management of medical supplies. These logistics benefits are especially important in healthcare because delivery delays may affect service quality and patient care.

Another major contribution of AI to HSCM is risk management and mitigation. Healthcare supply chains are exposed to several risks, including supply disruptions, quality failures, delivery delays, counterfeit products, cyber threats, regulatory issues, supplier failure, and demand shocks. Baryannis et al. (2019) highlighted the growing role of AI in supply chain risk management and identified its potential for improving risk prediction and mitigation. Chang et al. (2020) further showed that AI can support supply chain risk management by enabling earlier identification of risks and more proactive decision-making. In addition, Aljohani (2023) demonstrated that predictive analytics and machine learning can improve real-time supply chain risk mitigation and agility. These findings suggest that AI can strengthen the resilience, reliability, and continuity of healthcare supply chains.

Overall, the literature shows that AI has considerable potential to improve healthcare supply chain management through enhanced forecasting, inventory management, logistics optimisation, cost reduction, risk monitoring, and decision-making. However, successful AI application depends on more than the availability of AI technologies. It requires appropriate technological infrastructure, organisational readiness, and supportive environmental conditions. Although previous studies have examined AI in general SCM and healthcare contexts, limited empirical research has investigated the critical success factors influencing AI application in HSCM within the UAE, particularly in the context of Mubadala.

3. Conceptual Framework and Hypotheses Development

Artificial intelligence (AI) has increasingly become a strategic digital capability for improving supply chain management (SCM) performance. Through advanced analytics, machine learning, predictive modelling, optimisation algorithms, and real-time data processing, AI enables organisations to analyse large volumes of data, identify hidden patterns, improve decision accuracy, and respond more effectively to operational uncertainties. In supply chain contexts, AI has been widely recognised for its role in supporting demand forecasting, inventory control, logistics optimisation, risk management, and supply chain responsiveness (Pournader et al., 2021; Helo & Hao, 2022; Kumar et al., 2023). These capabilities make AI particularly relevant for organisations seeking to improve operational efficiency, resilience, and supply chain performance.

The importance of AI is especially significant in healthcare supply chain management (HSCM), where supply chain decisions directly affect service quality, patient safety, operational continuity, and the availability of critical medical supplies. Unlike many general supply chains, healthcare supply chains are characterised by demand uncertainty, strict service requirements, time-sensitive deliveries, regulatory obligations, and the need to maintain adequate stock levels for essential medicines, consumables, and medical equipment (Kwon et al., 2016; Kwon & Kim, 2018). These conditions make AI application valuable for improving the responsiveness, reliability, visibility, and resilience of HSCM operations (Bag et al., 2023; Bialas et al., 2023).

In the context of healthcare organisations in Mubadala, UAE, AI application may provide opportunities to address supply chain challenges by improving forecasting accuracy, reducing inventory inefficiencies, optimising logistics activities, and strengthening risk management capability. Empirical evidence suggests that AI-driven forecasting and decision-support systems can improve demand planning and reduce uncertainty in healthcare supply chains (Govindan et al., 2020; Jebbor et al., 2022; Seyedan & Mafakheri, 2020). Similarly, AI-enabled logistics and digital supply chain technologies can support transportation planning, resource allocation, visibility, tracking, and timely delivery of healthcare products (Trappey et al., 2018; Luong et al., 2020; Soumpenioti & Panagopoulos, 2023).

This study adopts the Technology–Organisation–Environment (TOE) framework to explain the critical success factors influencing AI application in HSCM. The TOE framework is appropriate because AI adoption does not depend only on technological availability, but also on organisational readiness and external environmental conditions. Therefore, this study proposes that technological factors, organisational factors, and environmental factors are key antecedents of AI application in healthcare supply chain management. AI application is then expected to influence four major HSCM outcomes: demand forecasting, inventory management, logistics optimisation, and risk management and mitigation.

Figure 1 presents the TOE-based conceptual framework of this study. The framework suggests that the successful application of AI in HSCM depends on the interaction of technological, organisational, and environmental factors. It also proposes that AI application serves as the central mechanism through which these critical success factors contribute to improved healthcare supply chain outcomes. The framework therefore provides the basis for developing and testing the hypotheses of this study.

3.1 Critical Success Factors and AI Application

The application of AI in HSCM depends first on the presence of appropriate technological conditions. Technological factors refer to the digital and technical resources required to support AI implementation. These include digital infrastructure, data availability, data quality, system integration, technical expertise, interoperability, and the compatibility of AI tools with existing healthcare supply chain systems. Healthcare organisations with stronger technological readiness are more likely to apply AI successfully because AI-based systems require accurate data, reliable platforms, integrated information systems, and sufficient analytical capability. Prior studies have emphasised that AI, big data analytics, and digital technologies enhance healthcare supply chain decision-making when organisations possess the technical capacity to implement and use them effectively (Hazen et al., 2014; Bag et al., 2023; Bialas et al., 2023). Therefore, this study proposes the following hypothesis:

H1: Technological factors have a significant positive influence on AI application in healthcare supply chain management.

Organisational factors also play an important role in AI application. These factors include top management support, employee readiness, financial resources, organisational culture, staff competence, training, and commitment to digital transformation. Even when AI technologies are available, successful application depends on whether the organisation has the leadership support, internal capabilities, human resources, and financial commitment needed to integrate AI into supply chain activities. The TOE perspective emphasises that organisational readiness is a key determinant of technology adoption, while healthcare supply chain studies show that effective organisational practices and internal capabilities are necessary for improving supply chain performance (Tornatzky et al., 1990; Al Hadwer et al., 2021; Hussain et al., 2020). Hence, the following hypothesis is proposed:

H2: Organisational factors have a significant positive influence on AI application in healthcare supply chain management.

Environmental factors may further shape AI application in HSCM. These factors include regulatory requirements, competitive pressure, supplier relationships, stakeholder expectations, market uncertainty, institutional pressure, and external supply chain disruptions. In healthcare, environmental pressures are especially important because organisations must ensure compliance, service continuity, product safety, and reliable access to critical medical supplies. Prior studies indicate that environmental uncertainty, healthcare supply chain disruptions, and institutional pressures can influence the adoption of digital and AI-enabled solutions for resilience and risk management (Al Badi et al., 2021; Ivanov & Dolgui, 2020; Aljohani, 2023). Therefore, this study hypothesises that:

H3: Environmental factors have a significant positive influence on AI application in healthcare supply chain management.

3.2 AI Application and Healthcare Supply Chain Management Outcomes

After AI is adopted and applied in HSCM, it is expected to improve key healthcare supply chain outcomes. One of the most important areas is demand forecasting. Accurate demand forecasting is essential in healthcare because demand for medicines, equipment, consumables, and medical supplies can fluctuate due to patient needs, emergencies, seasonal patterns, disease outbreaks, and service delivery requirements. AI-based forecasting models use historical data, real-time information, and advanced algorithms, including machine learning and deep learning, to identify complex demand patterns that traditional statistical methods may fail to capture. Empirical studies have shown that predictive analytics and AI-based forecasting models can improve forecasting accuracy and support better demand management in supply chains, including healthcare contexts (Seyedan & Mafakheri, 2020; Govindan et al., 2020; Jebbor et al., 2022). Based on this argument, the study proposes that:

H4: AI application has a significant positive influence on demand forecasting in healthcare supply chain management.

AI application is also expected to improve inventory management. Inventory management is critical in HSCM because shortages of essential medical supplies can disrupt healthcare delivery, while excess inventory can increase storage costs, waste, and product expiration risks. AI can support inventory management by improving demand visibility, generating more accurate reorder decisions, predicting stock requirements, and enabling real-time adjustment of inventory levels. Previous studies have shown that data-driven forecasting, collaborative inventory practices, and AI-enabled healthcare supply chain systems can reduce stockouts, minimise excess inventory, and improve inventory-related cost efficiency (Friday et al., 2021; Kumar et al., 2020; Essila, 2023). Therefore, the following hypothesis is proposed:

H5: AI application has a significant positive influence on inventory management in healthcare supply chain management.

In addition, AI application can enhance logistics optimisation. Logistics activities in healthcare supply chains involve transportation planning, routing, delivery scheduling, distribution coordination, tracking, and the timely movement of medical supplies. AI-driven optimisation tools can analyse logistics data and recommend efficient routes, delivery schedules, and resource allocation decisions. Prior studies have shown that the integration of AI, IoT, and advanced information technologies can improve logistics coordination, tracking, medical consumables management, and distribution efficiency in healthcare supply chains (Trappey et al., 2018; Luong et al., 2020; Soumpenioti & Panagopoulos, 2023). These improvements are important in HSCM because delays in the delivery of critical supplies may affect operational efficiency, service quality, and patient care. Hence, this study hypothesises that:

H6: AI application has a significant positive influence on logistics optimisation in healthcare supply chain management.

Finally, AI application is expected to strengthen risk management and mitigation in HSCM. Healthcare supply chains are exposed to several risks, including supply disruptions, quality problems, delivery delays, demand shocks, supplier failure, counterfeit products, cybersecurity threats, and regulatory challenges. AI-powered analytics can detect potential risks earlier, assess their likely impact, and support proactive mitigation strategies. Prior studies have established the role of AI in supply chain risk management, resilience, and disruption response (Baryannis et al., 2019; Chang et al., 2020; Ivanov & Dolgui, 2020). Similarly, predictive analytics and machine learning have been shown to improve real-time risk mitigation and supply chain agility, while cybersecurity-oriented Supply Chain 4.0 research highlights the importance of protecting digital supply chain systems (Aljohani, 2023; Sobb et al., 2020). Therefore, the study proposes that:

H7: AI application has a significant positive influence on risk management and mitigation in healthcare supply chain management.

Overall, the conceptual framework suggests that technological, organisational, and environmental factors are critical success factors for AI application in healthcare supply chain management. It further proposes that AI application improves key HSCM outcomes, including demand forecasting, inventory management, logistics optimisation, and risk management and mitigation. The proposed hypotheses will be empirically tested using data collected from healthcare organisations in Mubadala, UAE.

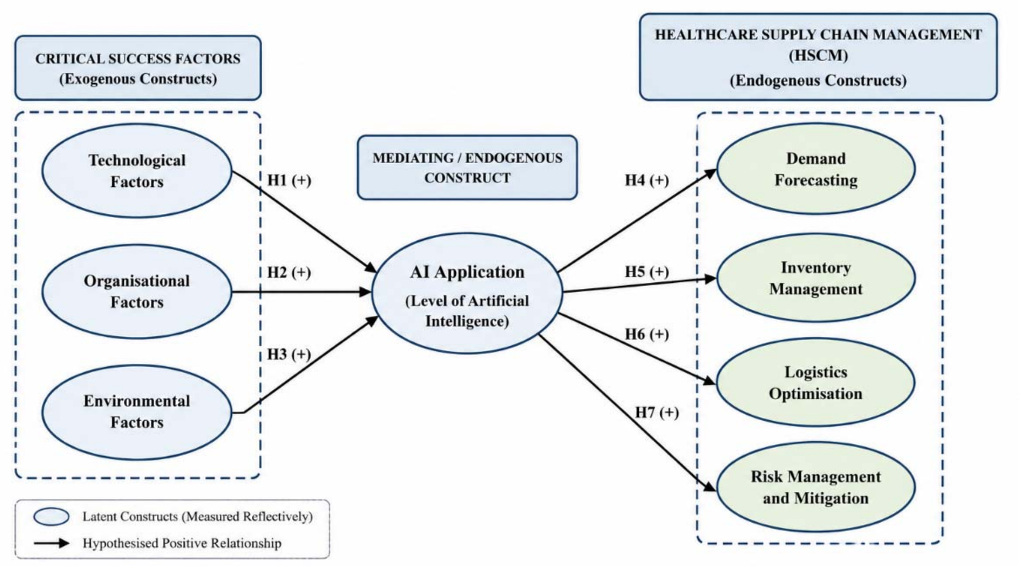

Figure 1. TOE-based conceptual framework for AI application in healthcare supply chain management

Figure 1 illustrates the proposed conceptual framework based on the Technology–Organisation–Environment (TOE) perspective. The framework shows that **technological factors**, **organisational factors**, and **environmental factors** are critical success factors that positively influence **AI application** in healthcare supply chain management. AI application is then proposed to improve four key healthcare supply chain outcomes: **demand forecasting**, **inventory management**, **logistics optimisation**, and **risk management and mitigation**.

4. Modelling of the Framework

The conceptual framework of this study was modelled based on the hypothesised relationships among the study constructs, as presented in Figure 2. The framework was developed to explain how critical success factors influence AI application and how AI application subsequently affects key dimensions of healthcare supply chain management (HSCM). Consistent with the Technology–Organisation–Environment perspective, the framework identifies technological, organisational, and environmental factors as antecedents of AI application (Tornatzky et al., 1990; Al Hadwer et al., 2021). This is also consistent with recent studies which emphasise the importance of technological readiness, organisational capability, and external environmental pressure in the adoption and implementation of AI-enabled healthcare supply chain systems (Al Badi et al., 2021; Kumar et al., 2023).

The model comprises both exogenous and endogenous constructs. The exogenous constructs are Technological Factors, Organisational Factors, and Environmental Factors, while AI Application serves as the central endogenous construct influenced by these critical success factors. In turn, AI Application is modelled as a predictor of four HSCM outcome dimensions: Demand Forecasting, Inventory Management, Logistics Optimisation, and Risk Management and Mitigation. These dimensions were included because previous studies have shown that AI can improve healthcare supply chain performance through better forecasting, inventory control, logistics coordination, and risk management capability (Govindan et al., 2020; Jebbor et al., 2022; Bag et al., 2023; Chang et al., 2020).

All variables in the framework were specified as latent constructs and measured using multiple indicators designed to capture their underlying theoretical meanings. In this study, the constructs were modelled reflectively, implying that the observed indicators are manifestations of their respective latent constructs. Therefore, changes in a latent construct are expected to be reflected in changes in its measurement indicators. Both the exogenous and endogenous constructs were therefore measured reflectively by their respective indicators.

Overall, the framework was confined to the direct relationships tested in the hypotheses. It shows that technological, organisational, and environmental factors influence AI Application, while AI Application influences Demand Forecasting, Inventory Management, Logistics Optimisation, and Risk Management and Mitigation in HSCM. This modelling approach ensures consistency between the conceptual framework, the hypotheses, and the structural model results.

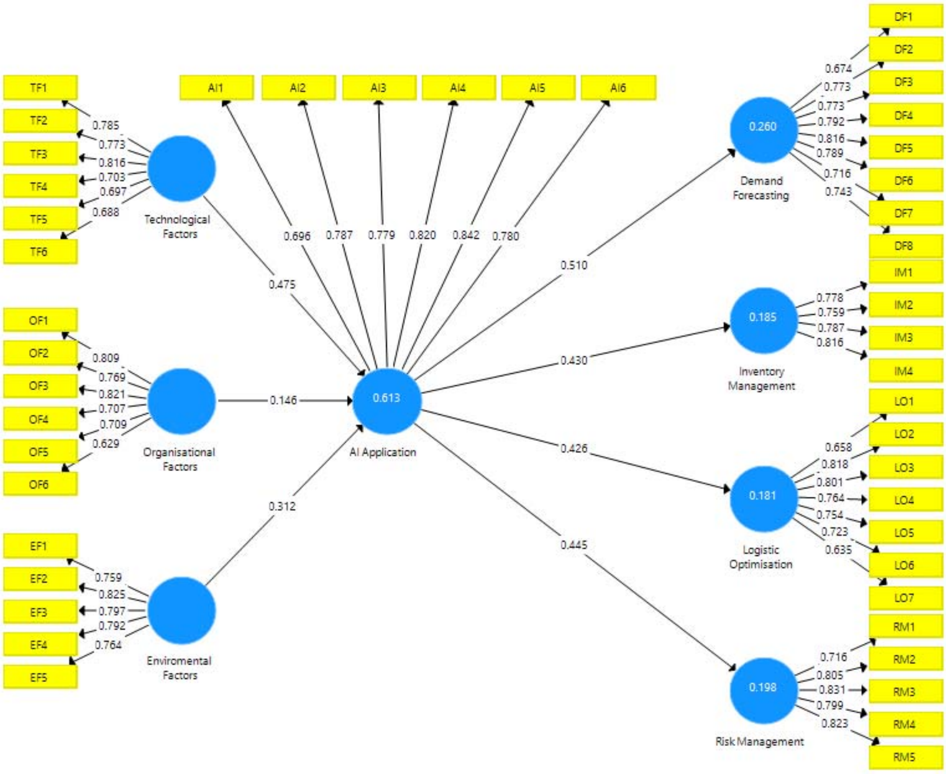

Figure 2. PLS-SEM model of the framework

4.1 Assessment of Measurement Model

The measurement model was assessed to determine the reliability and validity of the constructs used in the study. In PLS-SEM, the assessment of the measurement model is an essential prerequisite before evaluating the structural model because it confirms whether the indicators adequately measure their respective latent constructs (Hair et al., 2022). For reflective measurement models, reliability and validity are commonly examined using internal consistency reliability, convergent validity, and discriminant validity (Hair et al., 2019; Hair et al., 2022).

In this study, composite reliability and Average Variance Extracted (AVE) were used to assess internal consistency reliability and convergent validity, respectively. Composite reliability evaluates the extent to which the indicators of a construct consistently measure the same latent variable, while AVE assesses the proportion of variance captured by a construct in relation to the variance attributable to measurement error (Fornell & Larcker, 1981; Hair et al., 2022). In addition, the Heterotrait–Monotrait Ratio (HTMT) was used to assess discriminant validity, as it is considered a more reliable criterion for establishing the distinctiveness of constructs in PLS-SEM (Henseler et al., 2015).

4.1.1 Composite Reliability and Convergent Validity

Composite reliability and Average Variance Extracted were examined to establish the internal consistency reliability and convergent validity of the constructs. In PLS-SEM, a composite reliability value of 0.70 or above indicates satisfactory internal consistency reliability, while an AVE value of 0.50 or above demonstrates adequate convergent validity (Hair et al., 2019; Hair et al., 2022). These thresholds suggest that the indicators have sufficient shared variance and consistently represent their underlying constructs.

As shown in Table 1, all constructs recorded composite reliability values above the recommended threshold of 0.70. The values ranged from 0.866 to 0.916, indicating strong internal consistency reliability across the constructs. Similarly, all AVE values exceeded the minimum acceptable threshold of 0.50, with values ranging from 0.546 to 0.633. These results confirm that the constructs achieved adequate convergent validity, as their indicators explain a sufficient proportion of variance in the corresponding latent variables.

Table 1. Composite reliability

Constructs	Composite Reliability	Average Variance Extracted (AVE)
AI Application	0.906	0.617
Demand Forecasting_	0.916	0.579
Environmental Factors	0.891	0.621
Inventory Management	0.866	0.617
Logistic Optimisation	0.893	0.546
Organisational Factors	0.881	0.553
Risk Management	0.896	0.633
Technological Factors	0.882	0.555

Overall, the findings indicate that the measurement model satisfies the requirements for internal consistency reliability and convergent validity. Therefore, the constructs were considered reliable and valid for further analysis in the structural model.

4.1.2 Discriminant Validity

Discriminant validity was assessed using the Heterotrait–Monotrait Ratio of correlations (HTMT). Discriminant validity refers to the extent to which a construct is empirically distinct from other constructs in the model. Establishing discriminant validity is important in PLS-SEM because it confirms that each latent construct measures a unique concept and does not overlap excessively with other constructs (Hair et al., 2021; Hair et al., 2022).

The HTMT criterion is widely recommended for assessing discriminant validity because it provides a more sensitive and reliable assessment of construct distinctiveness than traditional methods such as the Fornell–Larcker criterion and cross-loadings (Henseler et al., 2015). According to Hair et al. (2021), HTMT values below 0.90 indicate that discriminant validity has been established. In more conservative assessments, a threshold of 0.85 may also be applied, particularly when constructs are conceptually distinct; however, the 0.90 threshold is commonly accepted in PLS-SEM studies involving related constructs.

As presented in Table 2, all HTMT values were below the recommended threshold of 0.90. This indicates that discriminant validity was successfully established among the constructs. The highest HTMT value was recorded between Demand Forecasting and Inventory Management (0.858) , followed by Logistic Optimisation and Demand Forecasting (0.842) . Although these values were relatively high, they remained within the acceptable threshold, suggesting that the constructs are sufficiently distinct from one another.

Table 2. HTMT measure of discriminant validity

Constructs	**AI Application**	**Demand Forecasting**	**Environmental Factors**	**Inventory Management**	**Logistic Optimisation**	**Organisational Factors**	**Risk Management**	**Technological Factors**
AI Application	—							
Demand Forecasting	0.573	—						
Environmental Factors	0.726	0.563	—					
Inventory Management	0.498	0.858	0.489	—				
Logistic Optimisation	0.476	0.842	0.498	0.797	—			
Organisational Factors	0.609	0.463	0.562	0.404	0.452	—		
Risk Management	0.514	0.803	0.586	0.691	0.817	0.342	—	
Technological Factors	0.800	0.481	0.565	0.488	0.366	0.610	0.373	—

Therefore, the results confirm that each construct in the measurement model represents a unique theoretical concept. This implies that the indicators used to measure the constructs are not excessively overlapping and that the measurement model satisfies the requirement for discriminant validity. Consequently, the model was considered suitable for further structural model assessment.

4.2 Structural Model Evaluation

Following the assessment of the measurement model, the next stage in the PLS-SEM analysis was the evaluation of the structural model. The structural model assessment was conducted to examine the predictive power of the model and to determine the strength and significance of the hypothesised relationships among the constructs. In PLS-SEM, structural model evaluation commonly involves assessing the coefficient of determination (R^2), effect size (f^2), and path coefficients, including their statistical significance (Hair et al., 2021; Hair et al., 2022).

In this study, the coefficient of determination (R^2) was used to determine the extent to which the exogenous constructs explain the variance in the endogenous constructs. The effect size

(f^2) was assessed to determine the relative contribution of each predictor construct to the explanatory power of the model. In addition, the path coefficients were examined to determine the direction, strength, and significance of the hypothesised relationships among the constructs.

The significance of the structural paths was assessed using the bootstrapping procedure with 5,000 subsamples, as recommended in PLS-SEM analysis (Hair et al., 2022). The analysis was conducted at a 5% level of significance, and the percentile confidence interval method was applied to evaluate the statistical significance of the hypothesised relationships. Figure 3 presents the structural model, showing the t-values associated with the path coefficients.

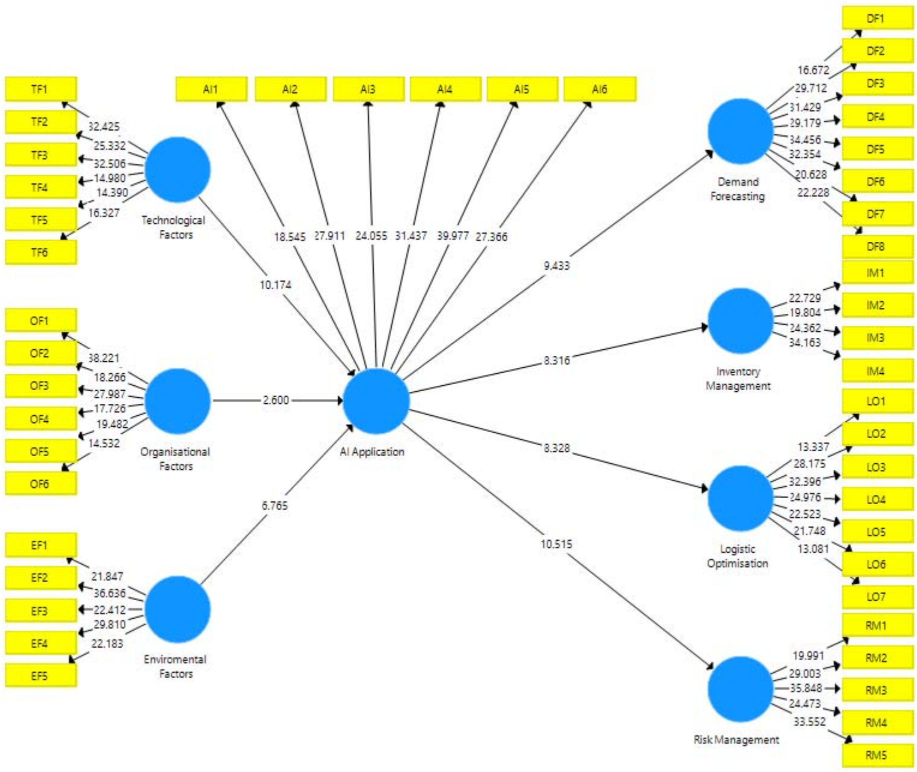

Figure 3. Structural model path

4.2.1 R-Square

The coefficient of determination (R^2) was assessed to determine the explanatory power of the structural model. In PLS-SEM, R^2 indicates the proportion of variance in an endogenous construct that is explained by its predictor constructs (Hair et al., 2014; Hair et al., 2015; Hair et al., 2022). Although there is no universal rule for judging acceptable R^2 values because explanatory power often depends on the research context, Hair, Ringle, and Sarstedt (2011) suggested that R^2 values of 0.25, 0.50, and 0.75 may be interpreted as weak, moderate, and substantial, respectively. Similarly, Ozili (2023) noted that R^2 values between 0.10 and 0.50

may be considered acceptable in social and management science research.

Table 3. R-square

Construct	R Square	R Square Adjusted
AI Application	0.613	0.610
Demand Forecasting	0.260	0.258
Inventory Management	0.185	0.183
Logistic Optimisation	0.181	0.179
Risk Management	0.198	0.195

As presented in Table 3, the R^2 value for AI Application was 0.613. This indicates that Technological Factors, Organisational Factors, and Environmental Factors jointly explained 61.3% of the variance in AI Application. Based on the recommended thresholds, this represents a moderate to substantial level of explanatory power, suggesting that the three critical success factors are important predictors of AI Application in healthcare supply chain management.

Furthermore, AI Application explained 26.0% of the variance in Demand Forecasting, 18.5% in Inventory Management, 18.1% in Logistics Optimisation, and 19.8% in Risk Management. These values suggest that AI Application has relatively weak but acceptable explanatory power for the HSCM dimensions, particularly within the context of social and management science research. Among the four HSCM outcomes, Demand Forecasting recorded the highest R^2, indicating that AI Application explains more variance in forecasting-related activities than in the other supply chain dimensions.

4.2.2 Effect Size (f2)

Effect size f^2 was assessed to determine the relative contribution of each predictor construct to the R^2 value of the corresponding endogenous construct. While R^2 explains the overall predictive power of the model, f^2 shows the extent to which a specific exogenous construct contributes to that predictive power when included in the model (Hair et al., 2022). Thus, f^2 provides additional insight into the substantive importance of each predictor construct.

Cohen's (1988) guidelines were used to interpret the f^2 values. According to these guidelines, f^2 values of 0.02, 0.15, and 0.35 indicate small, medium, and large effects, respectively. Therefore, a higher f^2 value indicates that the predictor construct makes a stronger contribution to explaining the variance in the endogenous construct.

Table 4. Effect sizes

	AI Application	Demand Forecasting	Inventory Management	Logistic Optimisation	Risk Management
AI Application		0.351	0.227	0.222	0.247
Environmental Factors	0.168				
Organisational Factors	0.036				
Technological Factors	0.379				

As shown in Table 4, AI Application had a large effect on Demand Forecasting ($f^2 = 0.351$) . This indicates that AI Application makes a strong contribution to explaining changes in demand forecasting within healthcare supply chain management. AI Application also had medium effects on Inventory Management ($f^2 = 0.227$), Logistics Optimisation ($f^2 = 0.222$), and Risk Management ($f^2 = 0.247$). These results suggest that AI Application contributes meaningfully to the improvement of key HSCM outcomes.

Regarding the predictors of AI Application, Technological Factors recorded a large effect ($f^2 = 0.379$), indicating that technological readiness is the strongest contributor to AI Application in the model. Environmental Factors recorded a medium effect ($f^2 = 0.168$), while Organisational Factors recorded a small effect ($f^2 = 0.036$). This suggests that technological and environmental conditions play more influential roles in AI Application than organisational factors. Overall, the f^2 results support the importance of AI Application in improving HSCM outcomes and highlight technological readiness as the most influential antecedent of AI Application.

4.2.3 Path Coefficients

The assessment of path coefficients was conducted to determine the strength, direction, and statistical significance of the hypothesised relationships in the structural model. Path coefficients are represented by beta (β) values, where positive values indicate positive relationships between predictor and outcome constructs. In this study, the significance of the path coefficients was assessed using the t-statistics and p-values obtained from the bootstrapping procedure.

Table 5. Path coefficients

Direct Path	**Path Coefficient (β)**	**T Statistics**	**P Values**
AI Application → Demand Forecasting	0.510	9.433	0.000
AI Application → Inventory Management	0.430	8.316	0.000
AI Application → Logistic Optimisation	0.426	8.328	0.000
AI Application → Risk Management	0.445	10.515	0.000
Environmental Factors → AI Application	0.312	6.765	0.000
Organisational Factors → AI Application	0.146	2.600	0.009
Technological Factors → AI Application	0.475	10.174	0.000

As presented in Table 5, all hypothesised relationships were positive and statistically significant at the 5% level of significance. The strongest path was from AI Application to Demand Forecasting ($\beta = 0.510$, $t = 9.433$, $p < 0.001$). This indicates that AI application has a strong positive influence on demand forecasting in healthcare supply chain management. The result suggests that AI-enabled analytics, machine learning, and predictive modelling can improve the ability of healthcare organisations to anticipate demand patterns and plan medical supplies more accurately. This finding is consistent with prior studies which show that AI-based forecasting and data-driven decision-support systems improve demand prediction and reduce uncertainty in supply chain operations (Seyedan & Mafakheri, 2020; Govindan et al., 2020; Jebbor et al., 2022).

The second strongest path was from Technological Factors to AI Application ($\beta = 0.475$, $t = 10.174$, $p < 0.001$). This finding shows that technological readiness is a major antecedent of AI application in HSCM. It implies that digital infrastructure, system compatibility, data availability, and technical capability are important conditions for the successful implementation of AI in healthcare supply chain operations. This result aligns with studies showing that AI and digital technologies require strong technological capacity, data quality, and interoperable systems to support effective supply chain decision-making (Hazen et al., 2014; Bag et al., 2023; Bialas et al., 2023).

AI Application also had a significant positive effect on Risk Management ($\beta = 0.445$, $t = 10.515$, $p < 0.001$). This suggests that AI helps healthcare organisations identify, assess, and respond to supply chain risks more effectively. Given the sensitivity of healthcare supply chains to disruptions, shortages, quality issues, and delivery delays, AI-enabled risk detection and predictive analytics can strengthen resilience and proactive decision-making. This finding supports previous studies which emphasise the role of AI in supply chain risk management, disruption response, and resilience building (Baryannis et al., 2019; Chang et al., 2020; Ivanov & Dolgui, 2020; Aljohani, 2023).

Furthermore, AI Application had significant positive effects on Inventory Management ($\beta = 0.430$, $t = 8.316$, $p < 0.001$) and Logistics Optimisation ($\beta = 0.426$, $t = 8.328$, $p < 0.001$). These findings indicate that AI application contributes to improved stock control, replenishment decisions, transportation planning, delivery scheduling, and distribution efficiency in HSCM. This is important because effective inventory and logistics management help healthcare organisations reduce stockouts, minimise wastage, improve timely delivery, and support continuity of care. These findings are consistent with studies showing that AI-based systems, predictive analytics, and advanced digital technologies improve inventory control, logistics coordination, and supply chain responsiveness (Kumar et al., 2020; Friday et al., 2021; Trappey et al., 2018; Luong et al., 2020; Soumpenioti & Panagopoulos, 2023).

Environmental Factors also had a significant positive effect on AI Application ($\beta = 0.312$, $t = 6.765$, $p < 0.001$). This implies that external conditions such as regulatory requirements, competitive pressure, stakeholder expectations, supply chain uncertainty, and the need for continuity in healthcare delivery influence AI application. In healthcare supply chains, environmental pressure may encourage organisations to adopt AI-enabled systems to improve visibility, compliance, resilience, and responsiveness. This result is consistent with studies which highlight the influence of external pressure, uncertainty, and institutional context on the adoption of AI and digital supply chain technologies (Al Badi et al., 2021; Ivanov & Dolgui, 2020; Aljohani, 2023).

Organisational Factors had the weakest but still significant positive effect on AI Application (β = 0.146, t = 2.600, p = 0.009). This indicates that management support, employee readiness, financial resources, organisational culture, and commitment to digital transformation contribute to AI application, although their influence is weaker than technological and environmental factors. This finding suggests that while internal organisational support is important, AI implementation in HSCM may depend more strongly on technological readiness and external pressures. The result is supported by studies showing that organisational readiness, managerial support, and effective organisational practices are important for successful technology adoption and healthcare supply chain performance (Tornatzky et al., 1990; Al Hadwer et al., 2021; Hussain et al., 2020).

Overall, the results confirm that AI Application significantly contributes to the improvement of HSCM dimensions, particularly Demand Forecasting, Risk Management, Inventory Management, and Logistics Optimisation. The findings also demonstrate that Technological Factors are the most influential antecedent of AI Application, followed by Environmental Factors and Organisational Factors. Therefore, the results provide empirical support for the proposed conceptual framework and confirm that AI application is an important mechanism for improving healthcare supply chain performance in Mubadala, UAE.

5. Discussion of the Findings

This section discusses the findings of the study based on the structural model results. The results show that all hypothesised relationships were positive and statistically significant. This indicates that **technological, organisational, and environmental factors** significantly influence **AI application in healthcare supply chain management (HSCM)**. The findings also show that AI application significantly improves four key HSCM outcomes: **demand forecasting, inventory management, logistics optimisation, and risk management**. Therefore, all seven hypotheses proposed in this study were supported.

These findings provide empirical support for the Technology–Organisation–Environment (TOE) framework in explaining the critical success factors for AI application in HSCM. They also support previous studies which suggest that AI and digital technologies can improve healthcare supply chain performance through better forecasting, improved visibility, enhanced decision-making, stronger inventory control, and more effective risk management capability (Bag et al., 2023; Kumar et al., 2023; Pournader et al., 2021).

The strongest relationship in the model was between **AI application and demand forecasting (β = 0.510, p < 0.001)**. This finding suggests that AI application plays a major role in improving forecasting capability in healthcare supply chain management. The positive coefficient indicates that greater use of AI is associated with better demand prediction. This is particularly important in healthcare supply chains, where inaccurate forecasting can lead to stockouts, overstocking, wastage, product expiration, and delays in the availability of essential medical supplies. The finding supports previous studies which argued that AI-driven forecasting and predictive analytics models improve demand prediction by processing large volumes of historical and real-time data and identifying complex demand patterns (Seyedan & Mafakheri, 2020; Govindan et al., 2020; Jebbor et al., 2022). Therefore, the result confirms that AI application can help healthcare organisations in Mubadala, UAE, improve planning accuracy and achieve better alignment between demand and supply.

The results also show that **AI application has a significant positive influence on inventory management ($\beta = 0.430$, $p < 0.001$)**. This finding implies that AI contributes meaningfully to better inventory control in healthcare supply chains. Through AI-enabled systems, healthcare organisations can monitor inventory levels, predict replenishment needs, reduce excess stock, minimise shortages, and improve stock visibility. This is important because inventory inefficiency in healthcare may result in increased costs, product expiration, wastage, and disruption of patient care. The finding is consistent with studies which show that AI-based forecasting, data quality, and collaborative inventory practices can improve stock control, reduce stockout risks, and enhance inventory-related efficiency in healthcare supply chains (Hazen et al., 2014; Kumar et al., 2020; Friday et al., 2021; Essila, 2023). Thus, AI application can strengthen inventory visibility and support more responsive inventory decisions in HSCM.

Furthermore, **AI application was found to have a significant positive influence on logistics optimisation ($\beta = 0.426$, $p < 0.001$)**. This result indicates that AI enhances logistics activities such as route planning, delivery scheduling, transportation coordination, distribution efficiency, and tracking of medical supplies. Although this coefficient is slightly lower than those reported for demand forecasting, inventory management, and risk management, the relationship remains statistically significant. This means that AI application still contributes positively to logistics performance in healthcare supply chains. The finding aligns with studies showing that AI, IoT, and advanced information technologies can improve logistics coordination, medical consumables management, tracking, and distribution efficiency (Trappey et al., 2018; Luong et al., 2020; Soumpenioti & Panagopoulos, 2023). In the healthcare context, logistics optimisation is especially important because delays in the movement of medical supplies can affect service delivery, operational continuity, and patient outcomes.

The findings also reveal that **AI application has a significant positive influence on risk management ($\beta = 0.445$, $p < 0.001$)**. This suggests that AI helps healthcare organisations identify, assess, and respond to supply chain risks more effectively. Healthcare supply chains are exposed to several risks, including supply disruptions, demand uncertainty, quality problems, delivery delays, counterfeit products, cybersecurity threats, and shortages of essential medical products. The positive relationship indicates that AI application can improve risk visibility, support early warning systems, and enable proactive mitigation strategies. This finding supports previous studies which show that AI and predictive analytics can improve supply chain risk management, disruption response, and resilience (Baryannis et al., 2019; Chang et al., 2020; Ivanov & Dolgui, 2020; Aljohani, 2023). It also reinforces the importance of AI-enabled risk detection for ensuring continuity and reliability in healthcare supply chains.

With respect to the antecedents of AI application, **technological factors had the strongest influence on AI application (β = 0.475, p < 0.001)**. This finding indicates that technological readiness is the most important critical success factor for AI application in the model. It implies that the availability of digital infrastructure, quality data systems, technical expertise, system compatibility, analytics capability, and integrated platforms strongly determines the extent to which AI can be applied in HSCM. This result is expected because AI depends heavily on reliable data, interoperable systems, and adequate technological infrastructure. The finding supports previous studies which emphasise that AI, big data analytics, and digital technologies require strong technical capability, data quality, and system integration to support effective supply chain decision-making (Hazen et al., 2014; Bag et al., 2023; Bialas et al., 2023).

Environmental factors also had a significant positive influence on AI application (β = 0.312, p < 0.001). This finding suggests that external pressures and environmental conditions influence the application of AI in healthcare supply chain management. Factors such as regulatory requirements, competitive pressure, supplier relationships, stakeholder expectations, market uncertainty, and supply chain disruptions may encourage healthcare organisations to adopt AI-based solutions. In the UAE healthcare context, external pressure for efficiency, transparency, service quality, and continuity of supply may motivate organisations to use AI to improve supply chain responsiveness. This finding is consistent with studies which highlight the role of institutional context, uncertainty, disruption risks, and external pressures in shaping the adoption of digital and AI-enabled supply chain solutions (Al Badi et al., 2021; Ivanov & Dolgui, 2020; Aljohani, 2023).

Organisational factors had the weakest, but still significant, influence on AI application (β = 0.146, p = 0.009). This finding indicates that organisational readiness, management support, staff competence, financial resources, training, and innovation culture contribute to AI application, although their effect is weaker compared with technological and environmental factors. The relatively low coefficient may suggest that, in the context of Mubadala, UAE, AI application in HSCM is more strongly driven by technological readiness and external pressures than by internal organisational conditions. Nevertheless, the significant result confirms that organisational support remains important for successful AI implementation. This finding is consistent with the TOE perspective, which identifies organisational readiness as an important condition for technology adoption, and with healthcare supply chain studies that emphasise the role of organisational practices in improving supply chain effectiveness (Tornatzky et al., 1990; Al Hadwer et al., 2021; Hussain et al., 2020).

Overall, the findings show that AI application is an important driver of healthcare supply chain improvement in Mubadala, UAE. Among the HSCM outcomes, AI had the strongest effect on **demand forecasting**, followed by **risk management**, **inventory management**, and **logistics optimisation**. This suggests that AI is particularly valuable in predictive and analytical supply chain functions, especially where large volumes of data are required to support accurate and timely decisions. The findings also show that **technological factors** are the most influential antecedent of AI application, followed by **environmental factors** and **organisational factors**. Therefore, healthcare organisations seeking to improve AI application in HSCM should prioritise investment in technological infrastructure, data integration, system compatibility, analytics capability, and staff competence, while also responding effectively to external regulatory and operational pressures.

6. Conclusion

This study examined the **critical success factors for artificial intelligence (AI) application in healthcare supply chain management (HSCM)** using the Technology–Organisation–Environment (TOE) framework, with specific focus on healthcare organisations in **Mubadala, UAE**. The study investigated how technological, organisational, and environmental factors influence AI application, and how AI application contributes to key HSCM outcomes, namely demand forecasting, inventory management, logistics optimisation, and risk management.

The findings provide empirical support for the proposed TOE-based conceptual framework. The results showed that technological, organisational, and environmental factors all have significant positive effects on AI application in HSCM. Among these factors, technological factors had the strongest influence, indicating that digital infrastructure, data availability, system compatibility, technical expertise, and analytics capability are essential requirements for successful AI application. This suggests that healthcare organisations must first build strong technological foundations before they can fully benefit from AI-enabled supply chain transformation.

Environmental factors also had a significant influence on AI application. This finding indicates that external pressures such as regulatory requirements, stakeholder expectations, market uncertainty, supplier relationships, and supply chain disruptions can encourage healthcare organisations to adopt AI-based solutions. In the UAE healthcare context, where service quality, supply continuity, innovation, and operational efficiency are important priorities, environmental conditions can play an important role in shaping AI adoption decisions.

Although organisational factors had the weakest effect, their significant influence confirms that internal organisational readiness remains important for effective AI application. Management support, employee readiness, financial resources, staff competence, training, and commitment to digital transformation are necessary to ensure that AI technologies are successfully integrated into healthcare supply chain processes. Therefore, AI implementation should not be viewed only as a technological initiative, but also as an organisational transformation process.

The study also found that AI application significantly improves key dimensions of healthcare supply chain management. AI application had the strongest effect on demand forecasting, followed by risk management, inventory management, and logistics optimisation. This indicates that AI is particularly valuable in predictive and analytical supply chain activities, where large volumes of data must be processed to support accurate and timely decision-making. The findings suggest that AI can help healthcare organisations improve demand prediction, optimise inventory levels, enhance logistics coordination, and identify supply chain risks more proactively.

Overall, the study concludes that AI application is an important driver of healthcare supply chain improvement in Mubadala, UAE. Effective AI application can strengthen the efficiency, responsiveness, reliability, and resilience of healthcare supply chains. By improving forecasting accuracy, inventory control, logistics planning, and risk management capability, AI can support the timely availability of medicines, medical devices, consumables, and other essential healthcare supplies, thereby contributing to better healthcare service delivery.

The study contributes to the growing literature on AI-enabled healthcare supply chain management by providing empirical evidence from the UAE context. It also extends the application of the TOE framework by demonstrating that technological, organisational, and environmental factors are important critical success factors for AI application in HSCM. From a practical perspective, the findings suggest that healthcare managers and supply chain professionals should prioritise investment in digital infrastructure, data integration, system interoperability, staff training, and organisational readiness. Policymakers and healthcare administrators should also create supportive regulatory and institutional environments that encourage responsible, secure, and effective AI adoption in healthcare supply chains.

Despite its contributions, this study has some limitations. The research focused on healthcare organisations in Mubadala, UAE, which may limit the generalisability of the findings to other healthcare systems or national contexts. Future studies could extend the research to other healthcare organisations across the UAE or conduct comparative studies across different countries. Further research may also examine additional outcomes of AI application, such as supplier performance, patient satisfaction, cost efficiency, service quality, cybersecurity readiness, and overall healthcare supply chain resilience.

References

Addy, A. (2023). *Artificial Intelligence in the Supply Chain Management for Vaccine Distribution in the West African Healthcare Sector with a focus on Ghana.*

Al Badi, F. K., Alhosani, K. A., Jabeen, F., Stachowicz-Stanusch, A., Shehzad, N., & Amann, W. (2021). Challenges of AI adoption in the UAE healthcare. *Vision: The Journal of Business Perspective*. https://doi.org/10.1177/0972262920988398

Al Hadwer, A., Tavana, M., Gillis, D., & Rezania, D. (2021). A systematic review of organizational factors impacting cloud-based technology adoption using Technology-Organization-Environment framework. *Internet of Things*, *15*, 100407. https://doi.org/10.1016/j.iot.2021.100407

Aljohani, A. (2023). Predictive analytics and machine learning for real-time supply chain risk mitigation and agility. *Sustainability*, *15*(20), 15088. https://doi.org/10.3390/su152015088

Bag, S., Dhamija, P., Singh, R. K., Rahman, M. S., & Sreedharan, V. R. (2023). Big data analytics and artificial intelligence technologies based collaborative platform empowering absorptive capacity in health care supply chain: An empirical study. *Journal of Business Research*, *154*, 113315. https://doi.org/10.1016/j.jbusres.2022.113315

Bag, S., Gupta, S., & Kumar, S. (2023). Artificial intelligence in healthcare supply chains: A review and future research agenda. *Technological Forecasting and Social Change*, *189*, 122312.

Bali, J., Garg, R., & Bali, R. T. (2019). Artificial intelligence in healthcare and biomedical research: Why a strong computational/AI bioethics framework is required? *Indian Journal of Ophthalmology*, *67*(1), 3–6. https://doi.org/10.4103/ijo.IJO_1292_18

Baryannis, G., Validi, S., Dani, S., & Antoniou, G. (2019). Supply chain risk management and artificial intelligence: State of the art and future research directions. *International Journal of Production Research*, *57*, 2179–2202. https://doi.org/10.1080/00207543.2018.1530476

Bialas, C., Revanoglou, A., & Manthou, V. (2023). Digitalization of the healthcare supply chain: Enterprise systems adoption and interoperability challenges. *Sustainability*, *15*(4), 3163. https://doi.org/10.3390/su15043163

Chang, Y., Wong, C. W. Y., & Choi, T. M. (2020). Artificial intelligence in risk management of supply chains. *International Journal of Production Research*, *58*(11), 3330–3346.

Chen, M., & Decary, M. (2020). Artificial intelligence in healthcare: An essential guide for health leaders. *Healthcare Management Forum*, *33*(1), 10–18. https://doi.org/10.1177/0840470419873123

Duan, Y., Edwards, J. S., & Dwivedi, Y. K. (2019). Artificial intelligence for decision making in the era of Big Data: Evolution, challenges and research agenda. *International Journal of Information Management*, *48*, 63–71. https://doi.org/10.1016/j.ijinfomgt.2019.01.021

Dubai Health Authority. (2018). *Dubai artificial intelligence strategy*. Dubai Health Authority.

Essila, J. C. (2023). Strategies for reducing healthcare supply chain inventory costs. *Benchmarking: An International Journal*, *30*(8), 2655–2669. https://doi.org/10.1108/BIJ-11-2021-0680

Friday, D., Savage, D. A., Melnyk, S. A., Harrison, N., Ryan, S., & Wechtler, H. (2021). A collaborative approach to maintaining optimal inventory and mitigating stockout risks during a pandemic: Capabilities for enabling health-care supply chain resilience. *Journal of Humanitarian Logistics and Supply Chain Management*, *11*(2), 248–271. https://doi.org/10.1108/JHLSCM-07-2020-0061

Govindan, K., Mina, H., & Alavi, B. (2020). A decision support system for demand management in healthcare supply chains considering epidemic outbreaks: A case study of COVID-19. *Transportation Research Part E: Logistics and Transportation Review*, *138*, 101967. https://doi.org/10.1016/j.tre.2020.101967

Hazen, B. T., Boone, C. A., Ezell, J. D., & Jones-Farmer, L. A. (2014/2016). Data quality for data science, predictive analytics, and big data in supply chain management. *International Journal of Production Economics*, *154*, 72–80. https://doi.org/10.1016/j.ijpe.2014.04.018

Hossain, M. K., Thakur, V., & Mangla, S. K. (2022). Modeling the emergency healthcare supply chains: Responding to the COVID-19 pandemic. *Journal of Business & Industrial Marketing*, *37*(8), 1623–1639. https://doi.org/10.1108/JBIM-07-2020-0315

Hussain, M., Al Hammadi, F., & Adebanjo, D. (2020). Adoption of practices for organizational effectiveness in healthcare supply chains: Insights from the United Arab Emirates. *International Journal of Productivity and Performance Management*. https://doi.org/10.1108/IJPPM-12-2018-0440

Ivanov, D., & Dolgui, A. (2020a). A digital supply chain twin for managing disruption risks and resilience in the era of Industry 4.0. *Production Planning & Control*, *31*(10), 962–976. https://doi.org/10.1080/09537287.2020.1768450

Ivanov, D., & Dolgui, A. (2020b). Viability of intertwined supply networks: Extending supply chain resilience angles towards survivability. *International Journal of Production Research*, *58*(10), 2904–2915. https://doi.org/10.1080/00207543.2020.1750727

Jebbor, S., Benabbou, L., & Berrado, A. (2022). Artificial intelligence for demand forecasting in healthcare supply chains. *Journal of Decision Systems*, *31*(3), 221–236.

Jebbor, S., Raddouane, C., & El Afia, A. (2022). A preliminary study for selecting the appropriate AI-based forecasting model for hospital assets demand under disasters. *Journal of Humanitarian Logistics and Supply Chain Management*, *12*(1), 1–29. https://doi.org/10.1108/JHLSCM-12-2020-0123

Kais, E. C. F., Ghafouri, A., & Al Shamsi, M. (2021). *A review of the impact of artificial intelligence on the healthcare industry: A United Arab Emirates perspective*.

Kaupa, F., & Naudé, M. J. (2021). Critical success factors in the supply chain management of essential medicines in the public health care system in Malawi. *Journal of Global Operations and Strategic Sourcing*, *14*(2), 210–231. https://doi.org/10.1108/JGOSS-01-2020-0004

Khan, R. S., Sirazy, M. R. M., Das, R., & Rahman, S. (2022). An AI and ML-enabled framework for proactive risk mitigation and resilience optimization in global supply chains during national emergencies. *Sage Science Review of Applied Machine Learning*, *5*(2), 127–144.

Kumar, A., Mani, V., Jain, V., Gupta, H., & Venkatesh, V. G. (2023). Managing healthcare supply chain through artificial intelligence: A study of critical success factors. *Computers & Industrial Engineering*, *175*, 108815. https://doi.org/10.1016/j.cie.2022.108815

Kumar, A., Singh, R. K., & Modgil, S. (2020). Exploring the relationship between AI techniques and supply chain performance in healthcare. *Journal of Business Research*, *116*, 534–545.

Kwon, I. W. G., & Kim, S. H. (2018). Framework for successful supply chain implementation in the healthcare area from provider's perspective. *Asia Pacific Journal of Innovation and Entrepreneurship*, *12*(2), 135–150. https://doi.org/10.1108/APJIE-04-2018-0024

Kwon, I. W. G., Kim, S. H., & Martin, D. G. (2016). Healthcare supply chain management: Strategic areas for quality and financial improvement. *Technological Forecasting and Social Change*, *113*, 422–428. https://doi.org/10.1016/j.techfore.2016.07.014

Luong, N. T., Luong, L. T., & Tuan, L. T. (2020). Integration of artificial intelligence and internet of things in logistics and supply chain management. *International Journal of Supply Chain Management*, *9*(1), 1–11.

Madancian, M., & Taherdoost, H. (2023). *The impact of artificial intelligence on human resource management: Opportunities and challenges*. https://doi.org/10.1007/978-3-031-54671-6_30

McDougall, R. J. (2019). Computer knows best? The need for value-flexibility in medical AI. *Journal of Medical Ethics*, *45*(3), 156–160. https://doi.org/10.1136/medethics-2018-105118

Nazzal, A. (2018). *Dubai Health Authority unveils AI strategy at the 7th DHA Transformation Forum*. Gulf News / DHA coverage.

Reddy, S., Fox, J., & Purohit, M. P. (2019). Artificial intelligence-enabled healthcare delivery. *Journal of the Royal Society of Medicine*, *112*(1), 22–28. https://doi.org/10.1177/0141076818815510

Roscoe, S., Skipworth, H., Aktas, E., & Habib, F. (2020). Managing supply chain uncertainty arising from geopolitical disruptions: Evidence from the pharmaceutical industry and Brexit. *International Journal of Operations & Production Management*, *40*(9), 1155–1185. https://doi.org/10.1108/IJOPM-10-2019-0668

Sardi, A., Sorano, E., Tradori, V., & Ceruzzi, P. (2024). Performance measurement and critical success factors: A case study of a national health service. *International Journal of Productivity and Performance Management*, *73*(11), 270–293. https://doi.org/10.1108/IJPPM-05-2023-0238

Seyedan, M., & Mafakheri, F. (2020). Predictive big data analytics for supply chain demand forecasting: Methods, applications, and research opportunities. *Journal of Big Data*, *7*(1), 53. https://doi.org/10.1186/s40537-020-00329-2

Sobb, T., Turnbull, B., & Moustafa, N. (2020). Supply Chain 4.0: A survey of cybersecurity challenges, solutions and future directions. *Electronics*, *9*(11), 1864. https://doi.org/10.3390/electronics9111864

Soumpenioti, V., & Panagopoulos, A. (2023). *AI technology in the field of logistics*. In 2023 18th International Workshop on Semantic and Social Media Adaptation & Personalization. https://doi.org/10.1109/SMAP59435.2023.10255203

Sun, T. Q., & Medaglia, R. (2019). Mapping the challenges of artificial intelligence in the public sector: Evidence from public healthcare. *Government Information Quarterly*, *36*(2), 368–383. https://doi.org/10.1016/j.giq.2018.09.008

Tornatzky, L. G., Fleischer, M., & Chakrabarti, A. K. (1990). *The processes of technological innovation.* Lexington Books.

Trappey, A. J. C., Trappey, C. V., & Li, R. (2018). Advanced information technologies for managing healthcare supply chain: A case study of medical consumables logistics management in Taiwan hospitals. *International Journal of Production Economics*, *197*, 156–166.

Trappey, C., Trappey, A., Hsiao, D., & Lin, Y. (2018). A blockchain-based provenance system for medical product supply chains. *Journal of Medical Systems*, *42*, Article 227.

Venkatesh, V., Morris, M. G., Davis, F. D., & Davis, G. B. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly*, *27*(3), 425–478. https://doi.org/10.2307/30036540

World Health Organization. (2019). *Supporting the development and strengthening of procurement and supply management systems*.

Zhang, X., Li, Y., & Wang, J. (2023). Smart vehicle deployment and tracking automation for healthcare supply chains. *Journal of Advanced Transportation*.

Copyrights