

The Mediating Role of Supply Chain Agility in the Impact of Artificial Intelligence on Supply Chain Management Success in the Healthcare Sector of Mubadala, UAE

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Abstract

In an era where digital transformation is redefining healthcare operations, understanding how emerging technologies like artificial intelligence (AI) enhance supply chain effectiveness is both timely and critical. This study investigates the mediating role of supply chain agility in the relationship between AI application and supply chain performance outcomes within the healthcare sector of Mubadala, UAE. A quantitative design was adopted, drawing on 305 valid survey responses from employees across Mubadala healthcare facilities. Using Partial Least Squares Structural Equation Modelling (PLS-SEM), the results reveal that AI Application Elements have a strong positive effect on Supply Chain Agility ($\beta = 0.614$) and a moderate direct impact on Supply Chain Performance Outcomes ($\beta = 0.332$). Supply Chain Agility also demonstrates a significant positive influence on performance outcomes ($\beta = 0.438$) and partially mediates the relationship between AI and performance (indirect effect $\beta = 0.269$). This study makes a key contribution by empirically validating a digital transformation model that integrates AI capabilities with operational agility to drive measurable improvements in healthcare supply chains. It offers practical insights for

decision-makers seeking to enhance supply chain responsiveness and efficiency in rapidly evolving healthcare environments.

Keywords: Artificial Intelligence, Supply Chain Agility, Supply Chain Management Success, Healthcare Sector, Mubadala, UAE

1. Introduction

Mubadala Health, a subsidiary of Mubadala Investment Company, is a prominent healthcare network in the United Arab Emirates (UAE), providing world-class medical care through a portfolio of integrated hospitals, clinics, and specialty centres (Mubadala Health Dubai, 2025). As part of the M42 health-tech ecosystem, Mubadala Health is strategically aligned with cutting-edge medical technologies and innovation to address complex healthcare demands across the region (Mubadala Health Dubai, 2025; Sophia, 2025).

At the heart of its operations lies Mubadala Health's Supply Chain Management (SCM) system, which ensures the continuous availability of pharmaceuticals, equipment, and clinical supplies essential to quality patient care. The SCM framework is designed to be centralized, responsive, and data-driven, managing procurement, inventory, logistics, and supplier coordination in a tightly regulated healthcare environment (Shaabania et al., 2025; Koornneef et al., 2012). This system plays a crucial role in supporting the organization's mission to deliver uninterrupted healthcare services, especially in times of disruption or emergency.

In recent years, Mubadala Health has proactively embraced Artificial Intelligence (AI) to enhance its supply chain capabilities. AI applications are now embedded across several functional areas, including demand forecasting, inventory optimization, logistics planning, and risk assessment. These technologies facilitate greater automation, predictive accuracy, and real-time decision-making across the supply chain (Umoren et al., 2025; Kumar, Goodarzian et al., 2025; Kaur & Prakash, 2025). For instance, AI-driven inventory management tools help reduce waste, optimize stock levels, and prevent shortages, while machine learning models enable predictive insights during supply chain disruptions (Karupiah et al., 2025; Adhikari et al., 2025).

Despite these advancements, Mubadala Health's supply chain faces persistent challenges. These include integration difficulties with legacy systems, limited AI maturity, data governance concerns, and dependency on international suppliers vulnerable to geopolitical or logistical disruptions (Cavadi, 2025; Alhajaj & Moonesar, 2023). Furthermore, high implementation costs and a shortage of AI-skilled talent remain key barriers to fully realizing the benefits of AI in healthcare SCM (Dewasiri et al., 2025; Kandhare et al., 2025). There are also regulatory and ethical concerns about the use of AI in managing sensitive healthcare data and decision-making processes (Bekbolatova et al., 2024; Shaheen, 2021).

While the literature has explored AI integration and SCM performance independently, gaps remain in understanding the mechanisms through which AI influences supply chain success in healthcare contexts. Specifically, the role of supply chain agility as a potential mediating factor is underexplored. Existing research has established that agile supply chains are more resilient and responsive during crises, yet few studies have examined how AI applications lead to improved agility in the healthcare sector (Mandal, 2018; Dubey, 2025; Rungtornsupattana & Jermittiparsert, 2019). Moreover, most studies are focused on general or Western healthcare systems, with limited insights from the Middle Eastern context, particularly in high-tech, integrated systems like Mubadala.

Therefore, this study intends to develop and validate a conceptual framework to examine the mediating role of supply chain agility in the relationship between Artificial Intelligence and supply chain management success within the healthcare sector of Mubadala, UAE. This framework bridges the current gap by contextualizing AI adoption within a dynamic healthcare environment, contributing to both academic knowledge and practical strategies for AI-enabled, resilient supply chain systems.

2. Literature Review for Framework

Mubadala Health Dubai, as part of the broader M42 healthcare network, plays a pivotal role in enhancing the digital and operational infrastructure of healthcare supply chain management (SCM) in the UAE. M42 is a global, tech-enabled healthcare company formed through the strategic merger of Mubadala Health, a UAE-based integrated healthcare network, and G42 Healthcare, an artificial intelligence (AI) and cloud computing company specializing in bioinformatics, digital health, and population genomics. This union leverages G42's technological and data science capabilities with Mubadala Health's extensive clinical and operational expertise to create an ecosystem capable of delivering highly efficient, patient-centred, and innovation-driven healthcare.

From a supply chain perspective, this merger enables real-time integration and synchronization across multiple nodes of the healthcare delivery system including hospitals, specialty centres, and diagnostic laboratories. The M42 platform oversees a wide portfolio of healthcare assets, such as Cleveland Clinic Abu Dhabi, Imperial College London Diabetes Centre (ICLDC), and Health point, which are geographically dispersed and require robust, interconnected supply chain operations. The digital backbone provided by G42 supports AI-powered demand forecasting, automated procurement, smart inventory management, and predictive logistics, all of which enhance supply chain visibility and agility (Umoren et al., 2025; Kumar et al., 2025).

Additionally, Mubadala Health Dubai's satellite facilities, which offer services in coordination with flagship institutions, rely heavily on multi-tiered supply chain coordination to ensure the availability of pharmaceuticals, medical devices, laboratory reagents, and surgical supplies. The use of AI and machine learning technologies allows for data-driven decision-making, improved resource allocation, and proactive disruption management, especially in response to public health crises or fluctuating demand patterns (Adhikari et al., 2025; Shashikumar, 2025). Thus, M42's integrated healthcare model not only advances clinical care but also serves as a foundational driver of an intelligent, resilient, and scalable healthcare supply chain framework aligned with the UAE's digital health strategy.

2.1 AI Application Elements in Healthcare

Artificial Intelligence (AI) is playing an increasingly vital role in enhancing supply chain management (SCM) within the healthcare sector. Key application areas include AI-based demand forecasting, AI-powered inventory management, AI-enabled risk management, and AI-driven logistics optimization. These applications align with the broader digital transformation trends in the healthcare industry and offer scalable, data-driven solutions to

complex operational challenges (Bohr & Memarzadeh, 2020; Väänänen et al., 2021).

AI-based Demand Forecasting improves accuracy in predicting future healthcare needs by analysing historical data, seasonal trends, and external variables such as pandemics or supply disruptions (Umoren et al., 2025; Kumar, Goodarzian et al., 2025). By anticipating demand, healthcare providers can ensure timely procurement and prevent shortages or overstocking. This aligns with the principles of proactive healthcare management and supports more agile responses to dynamic environments (Ibrahim & Baballe, 2024).

AI-powered Inventory Management enables real-time tracking and dynamic restocking of pharmaceuticals and medical equipment, reducing waste and optimizing storage space (Kaur & Prakash, 2025; Karuppiyah et al., 2025). These systems automate replenishment decisions based on data patterns, enhancing the efficiency of healthcare supply chains. Recent reviews have emphasized how AI enhances transparency and traceability in inventory systems, reducing both human error and supply risks (Shaheen, 2021; Saraswat et al., 2022).

AI-enabled Risk Management allows healthcare organizations to assess vulnerabilities, predict disruptions, and implement mitigation strategies through advanced machine learning models (Kumar, Sahoo et al., 2025; Tetteh et al., 2025). This is particularly valuable in disaster-prone or emergency healthcare settings where responsiveness is critical. Studies highlight that integrating AI into risk protocols leads to more resilient healthcare operations by facilitating early-warning systems and real-time decision-making (Bekbolatova et al., 2024; Drysdale et al., 2019).

AI-driven Logistics Optimization improves the efficiency of healthcare delivery networks by optimizing transport routes, minimizing delivery times, and reducing operational costs (Adhikari et al., 2025; Shashikumar, 2025). This also contributes to environmental sustainability by reducing emissions from healthcare logistics (Dewasiri et al., 2025). Such intelligent routing and dispatching systems are instrumental in enhancing last-mile delivery, particularly in decentralized care models (Saraswat et al., 2022).

Together, these AI applications contribute to building a resilient, data-driven, and patient-centred healthcare supply chain capable of responding effectively to both routine and crisis conditions. Mubadala Healthcare, through its integration with M42's advanced health-tech ecosystem, is actively leveraging AI across its supply chain operations to enhance accuracy, efficiency, and responsiveness. By adopting AI-enabled solutions in demand forecasting, inventory tracking, and logistics, Mubadala ensures that healthcare delivery is proactive and adaptive, aligning with its mission to provide world-class medical services in the UAE and beyond (Mubadala Health, 2025; Umoren et al., 2025).

Table 1. List of AI Application Elements

Code	AI Application	Description	Source(s)
AI01	AI-based Demand Forecasting	Uses historical data, seasonal trends, and external variables (e.g., pandemics) to improve prediction accuracy and support proactive procurement decisions.	Bohr & Memarzadeh (2020); Väänänen et al. (2021); Umoren et al. (2025); Kumar, Goodarzian et al. (2025); Ibrahim & Baballe (2024)
AI02	AI-powered Inventory Management	Enables real-time tracking and automated restocking of medicines and equipment, reducing waste and human error.	Kaur & Prakash (2025); Karuppiah et al. (2025); Shaheen (2021); Saraswat et al. (2022)
AI03	AI-enabled Risk Management	Identifies supply chain vulnerabilities, predicts disruptions, and informs mitigation strategies using machine learning algorithms.	Kumar, Sahoo et al. (2025); Tetteh et al. (2025); Bekbolatova et al. (2024); Drysdale et al. (2019)
AI04	AI-driven Logistics Optimization	Optimizes transportation routes and delivery schedules to reduce time, cost, and environmental impact; improves last-mile delivery efficiency.	Adhikari et al. (2025); Shashikumar (2025); Saraswat et al. (2022); Dewasiri et al. (2025)
AI05	Integrated AI in Health Systems	Combines AI technologies across forecasting, inventory, logistics, and risk to build resilient and responsive healthcare SCM platforms.	Mubadala Health (2025); Umoren et al. (2025)

2.2 Supply Chain Agility in Healthcare

Supply chain agility refers to the ability of a healthcare system to swiftly and effectively respond to unexpected changes in supply and demand conditions. In the healthcare sector, this agility is critical for ensuring uninterrupted access to essential medical supplies, pharmaceuticals, and equipment, particularly during emergencies or demand surges. Key elements of supply chain agility include the ability to rapidly adjust inventory levels based on patient inflow, quickly respond to supply chain disruptions such as global shortages or transportation delays, and maintain flexibility in adapting to fluctuations in demand across different medical services and departments (Patel & Sambasivan, 2022; Rouhani-Tazangi et al., 2023).

Additionally, the use of real-time data and advanced forecasting techniques supports timely and informed decision-making, further enhancing responsiveness. Scholars have emphasized that human capital, technological orientation, and collaborative networks are critical enablers of supply chain agility in healthcare settings (Mandal, 2018; Rungsisawat & Jermisittiparsert, 2019). For example, agile healthcare systems rely on well-trained personnel, integrated IT systems, and adaptive logistics infrastructures to quickly mobilize resources and navigate disruptions (Dubey, 2025; Talarposhti et al., 2016).

Mubadala Healthcare exemplifies these principles through its integrated and

technology-enabled supply chain approach, particularly under its collaboration with M42. The organization utilizes predictive analytics and data-driven systems to monitor and manage inventory dynamically, enabling rapid replenishment and reducing the risk of stockouts or excess. Moreover, Mubadala's ability to coordinate with local and international suppliers allows it to quickly mitigate the impact of external disruptions (Kumar et al., 2025; Adhikari et al., 2025). This level of agility ensures that Mubadala facilities continue to deliver uninterrupted, high-quality care while remaining resilient in the face of operational and environmental volatility (Mubadala Health, 2025).

Table 2. List of Supply Chain Agility Elements

Code	Element	Description	Source(s)
SCA01	Rapid Inventory Adjustment	Ability to swiftly adapt inventory levels based on fluctuating patient inflow and treatment needs.	Patel & Sambasivan (2022); Rouhani-Tazangi et al. (2023)
SCA02	Disruption Response Capability	Quick responsiveness to supply chain disruptions such as global shortages, delays, or emergencies.	Patel & Sambasivan (2022); Rouhani-Tazangi et al. (2023)
SCA03	Demand Flexibility	Flexibility in meeting changes in demand across medical services, departments, and specialties.	Patel & Sambasivan (2022); Rouhani-Tazangi et al. (2023)

2.3 Healthcare Supply Chain Performance Outcomes

An efficient healthcare supply chain directly influences organizational performance by reducing costs, enhancing service levels, and ensuring the timely delivery of medical products and services. Key performance indicators include cost reduction through streamlined procurement and inventory management, reduced stockouts that ensure continuity of patient care, improved delivery times that accelerate treatment processes, and enhanced service levels that reflect the reliability and responsiveness of supply chain operations (Mandal, 2018; Senna et al., 2024). These performance goals are essential for maintaining quality care while achieving operational sustainability.

Mubadala Healthcare, through its integration with M42, has implemented a performance-focused supply chain model that leverages digital platforms and artificial intelligence to drive continuous improvement. By optimizing inventory levels using predictive analytics, Mubadala minimizes excess inventory costs while reducing the risk of stockouts. Its data-driven logistics systems improve delivery efficiency across its network of hospitals and clinics, enabling timely access to essential medical supplies. Moreover, Mubadala's centralized procurement strategy enhances coordination across its facilities, contributing to improved service levels and patient satisfaction. These initiatives align with global best practices in healthcare supply chain management and position Mubadala as a leader in high-performance, value-driven healthcare delivery in the UAE (Tetteh et al., 2025;

Saha & Rathore, 2024).

Recent studies have underscored the growing role of supply chain risk management and counterfeit risk mitigation in driving healthcare supply chain performance, particularly in volatile environments (Senna et al., 2024; Falasca et al., 2022). Technologies associated with healthcare 4.0, including AI, IoT, and blockchain, are also proving essential in improving visibility and responsiveness across supply networks (Saha & Rathore, 2024; Hossain & Thakur, 2022). By embracing these technologies, organizations like Mubadala are better positioned to meet both operational and patient-centered performance outcomes.

Table 3. Supply Chain Performance Outcomes

Code	Performance Outcome	Description	Source(s)
O1	Cost Reduction	Achieved by streamlining procurement, reducing excess inventory, and optimizing resource use.	Mandal (2018); Senna et al. (2024)
O2	Reduced Stockouts	Ensures continuity of care by maintaining optimal inventory levels of critical medical supplies.	Tetteh et al. (2025); Saha & Rathore (2024)
O3	Improved Delivery Efficiency	Enhances speed and reliability of supply distribution, minimizing delays in patient treatment.	Hossain & Thakur (2022); Saha & Rathore (2024)
O4	Enhanced Service Levels	Reflects responsiveness and reliability of supply chain operations, improving patient satisfaction and outcomes.	Senna et al. (2024); Tetteh et al. (2025)

2.4 Development of Conceptual Framework

The conceptual framework for this study was developed to examine the mediating role of supply chain agility in the relationship between artificial intelligence (AI) applications and supply chain management (SCM) success within the healthcare sector, focusing specifically on Mubadala Health in the United Arab Emirates. This framework was grounded in a comprehensive review of literature on AI integration, healthcare operations, and the strategic importance of agility in supply chain systems.

Artificial intelligence technologies are increasingly adopted in healthcare supply chains to enhance responsiveness, efficiency, and precision. Applications such as AI-based demand forecasting, AI-driven logistics optimization, and AI-supported risk management have proven instrumental in streamlining supply chain processes and reducing operational bottlenecks (Dubey, 2025; Patel & Sambasivan, 2022). However, the successful implementation of these technologies depends on the organization's agility and its ability to adapt quickly to changing demand patterns, disruptions, or emergencies.

Supply chain agility, as defined in the literature, represents the capacity to respond rapidly and flexibly to both internal and external uncertainties in the supply environment. It plays a

crucial role in improving inventory visibility, mitigating the impact of supply disruptions, and sustaining service levels during volatile demand periods (Mandal, 2018; Rungtissawat & Jermittiparsert, 2019; Rouhani-Tazangi et al., 2023). This study positions supply chain agility as a mediating construct that facilitates the conversion of AI capabilities into concrete SCM outcomes, such as reliability, responsiveness, and cost-effectiveness.

The conceptual framework integrates three key constructs: AI application (independent variable), supply chain agility (mediator), and SCM success (dependent variable). AI application is operationalized through elements such as predictive analytics, smart inventory systems, and intelligent logistics planning. SCM success is evaluated based on criteria like lead time reduction, cost minimization, and service continuity. Supply chain agility serves as the enabler that connects technological investments with improved supply chain performance, consistent with findings from previous research (Talarposhti et al., 2016; Dubey, 2025).

Through aligning with Mubadala's digital health strategy and its emphasis on resilience and responsiveness, this framework offers a relevant and evidence-based approach to understanding how advanced technologies can be leveraged for healthcare SCM optimization. It also contributes to the academic discourse by empirically modelling agility as a dynamic capability that enhances the value derived from AI adoption in healthcare logistics systems. The proposed conceptual framework is shown in Figure 1.

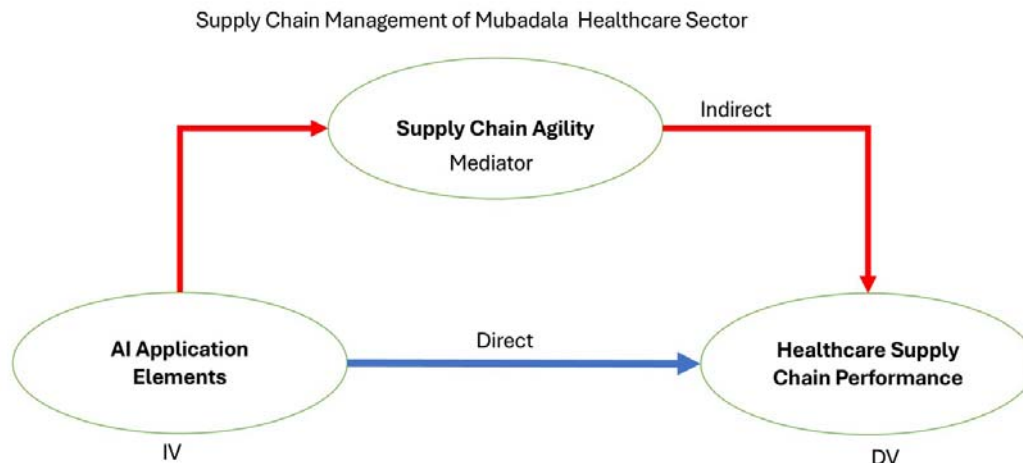


Figure 1. Proposed conceptual framework

Based on the conceptual framework diagram provided, the following three hypotheses can be formulated:

H1 (Direct Effect): AI Application Elements have a significant direct effect on Healthcare Supply Chain Performance. This hypothesis evaluates the direct influence of AI technologies on the success of supply chain operations within the healthcare sector.

H2 (Indirect Effect): AI Application Elements have a significant indirect effect on Healthcare

Supply Chain Performance through Supply Chain Agility. This hypothesis examines the extent to which the impact of AI on supply chain performance occurs indirectly via enhanced supply chain agility.

H3 (Partial Mediation Effect): Supply Chain Agility partially mediates the relationship between AI Application Elements and Healthcare Supply Chain Performance. This suggests that while AI applications influence supply chain performance directly, part of that effect is also channelled through improvements in supply chain agility, indicating a partial mediation.

3. Methodology

This study adopted a quantitative research approach to examine the mediating role of supply chain agility in the impact of artificial intelligence on supply chain management success within the healthcare sector of Mubadala, UAE. The quantitative design was considered appropriate for empirically testing the proposed conceptual framework and for evaluating the strength and significance of relationships among the key constructs.

Due to the lack of complete demographic information on the target population, the study employed a non-probability sampling strategy. Specifically, purposive and convenience sampling methods were adopted to ensure access to relevant participants who possessed knowledge and experience in Mubadala's healthcare supply chain. Memon et al. (2017) support this approach, recommending convenience sampling for quantitative research when full population data are not available. The target participants included employees working in managerial, logistics, and technical roles, as they were directly involved in healthcare supply chain operations.

Data were collected through a structured questionnaire distributed across various Mubadala healthcare facilities. In addition to capturing respondents' demographic information, the questionnaire comprised sections measuring three key constructs: AI application elements, supply chain agility, and healthcare supply chain performance outcomes. All items were assessed using a 5-point Likert scale indicating the degree of agreement with each statement. A total of 305 valid responses were obtained, providing a sufficient sample size for conducting robust statistical analysis. The collected data were then used to model and empirically validate the proposed conceptual framework, which integrates artificial intelligence applications, supply chain agility, and supply chain management success as the core components.

The study employed Partial Least Squares Structural Equation Modelling using SmartPLS software because of its suitability in dealing with complex models and its effectiveness with small to medium sample sizes, particularly in exploratory and predictive research. The analysis involved assessing the measurement model to ensure construct reliability and validity, including evaluating indicator loadings, composite reliability, and average variance extracted, along with discriminant validity using the heterotrait-monotrait (HTMT) ratio. Following this, the structural model was assessed to examine the direct and mediating relationships between the variables. Model fit and predictive relevance were also evaluated using R^2 , Q^2 , and the Goodness-of-Fit index.

This methodological process enabled the study to empirically validate the proposed framework and generate insights into how artificial intelligence applications and supply chain agility influence the overall success of supply chain management within the context of Mubadala's healthcare supply chain management system in the United Arab Emirates.

4. Modelling Analysis

To examine the hypothesised relationships among artificial intelligence application, supply chain agility, and supply chain management success, Partial Least Squares Structural Equation Modelling (PLS-SEM) was employed using the SmartPLS software. This approach was chosen for its suitability in predictive modelling, handling of complex frameworks, and its effectiveness with medium-sized samples (Hair et al., 2017; Sarstedt et al., 2020).

4.1 Measurement Model Evaluation

The modelling followed the widely accepted two-stage procedure. The first stage involved the assessment of the measurement model, where internal consistency was verified through Cronbach's Alpha and Composite Reliability (CR), ensuring values exceeded the threshold of 0.70 (Hair et al., 2019). Convergent validity was assessed via the Average Variance Extracted (AVE), with all constructs surpassing the recommended 0.50 benchmark. Discriminant validity was established using both the Fornell-Larcker criterion and Heterotrait-Monotrait (HTMT) ratios, confirming that constructs were distinct and not overly correlated (Henseler et al., 2015).

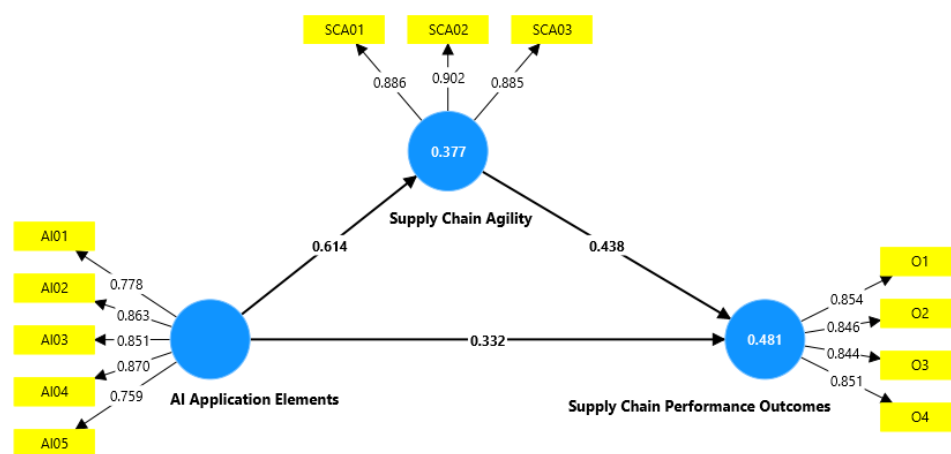


Figure 2. Model after PLS Algorithm procedure

Figure 2 shows the graphical results of the path analysis after applying the PLS Algorithm procedure. The results from this procedure are as follow;

Table 4. Construct reliability and validity

Constructs	Cronbach's alpha	Average Variance Extracted (AVE)
AI Application Elements	0.882	0.681
Supply Chain Agility	0.870	0.794
Supply Chain Performance Outcomes	0.871	0.720

As shown in Table 4, all constructs demonstrate strong internal consistency reliability and convergent validity. Specifically, Cronbach's alpha values for AI Application Elements (0.882), Supply Chain Agility (0.870), and Supply Chain Performance Outcomes (0.871) all exceed the recommended threshold of 0.70 (Hair et al., 2017), confirming reliability. Additionally, the Average Variance Extracted (AVE) values for AI Application Elements (0.681), Supply Chain Agility (0.794), and Supply Chain Performance Outcomes (0.720) are all above the 0.50 benchmark, indicating adequate convergent validity (Fornell & Larcker, 1981).

Table 5. HTMT

Constructs	AI Application Elements	Supply Chain Agility	Supply Chain Performance Outcomes
AI Application Elements			
Supply Chain Agility	0.700		
Supply Chain Performance Outcomes	0.686	0.736	

As shown in Table 5, the Heterotrait-Monotrait (HTMT) ratios between all pairs of constructs are below the conservative threshold of 0.85, indicating satisfactory discriminant validity (Henseler et al., 2015). Specifically, the HTMT value between AI Application Elements and Supply Chain Agility is 0.700, between AI Application Elements and Supply Chain Performance Outcomes is 0.686, and between Supply Chain Agility and Supply Chain Performance Outcomes is 0.736. These values support the conclusion that the constructs are empirically distinct from one another.

Table 6. Fornell Larcker criterion

Constructs	AI Application Elements	Supply Chain Agility	Supply Chain Performance Outcomes
AI Application Elements	0.825		
Supply Chain Agility	0.614	0.891	
Supply Chain Performance Outcomes	0.601	0.642	0.849

As presented in Table 6, the square roots of the AVE values are 0.825 for AI Application Elements, 0.891 for Supply Chain Agility, and 0.849 for Supply Chain Performance Outcomes. Each of these values is greater than the corresponding inter-construct correlations, specifically, 0.614 between AI Application Elements and Supply Chain Agility, 0.642 between Supply Chain Agility and Supply Chain Performance Outcomes, and 0.601 between AI Application Elements and Supply Chain Performance Outcomes. These results confirm that the Fornell-Larcker criterion is met, thereby establishing discriminant validity and affirming that each construct is statistically distinct from the others (Fornell & Larcker, 1981).

4.2 Structural Model Evaluation

The structural model was assessed by examining path coefficients, t-statistics, and p-values using bootstrapping with 5,000 subsamples to evaluate the significance of direct and indirect effects. R^2 values were used to determine the model's explanatory power, with values above 0.25 indicating moderate predictive ability. Additionally, effect sizes (f^2) and predictive relevance (Q^2) were calculated to assess the strength of predictors and the model's out-of-sample predictive accuracy.

4.2.1 Path Analysis

This involved evaluating path coefficients, t-statistics, and p-values generated through bootstrapping with 5,000 subsamples to assess the significance of both direct and indirect effects (Hair et al., 2017). As shown in Figure 3, the structural model illustrates the strength and direction of relationships between Artificial Intelligence (AI) applications, Supply Chain Agility (SCA), and Supply Chain Management Success (SCMS).

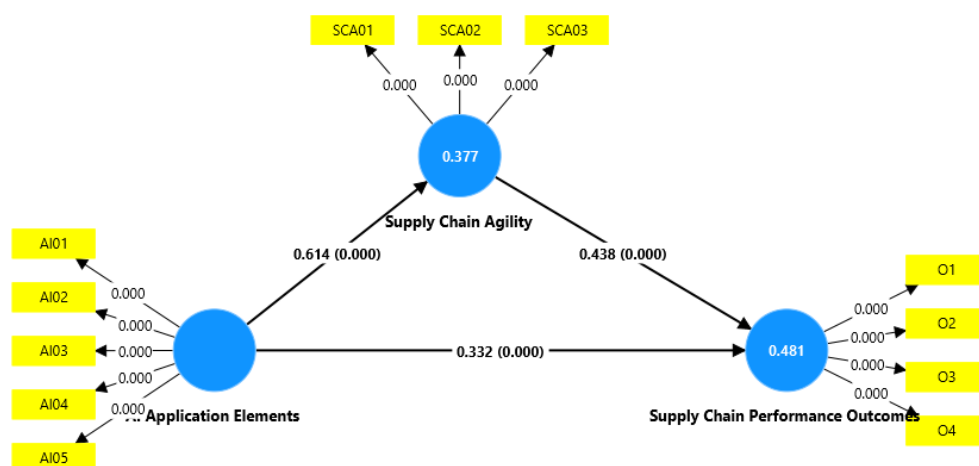


Figure 3. After bootstrapping procedure

Figure 3 displays the graphical results of the path analysis after applying the bootstrapping procedure. The model presents the relationships between AI Application Elements, Supply

Chain Agility, and Supply Chain Performance Outcomes, with path coefficients and significance values.

Table 7. Direct

Direct relationship	Path strength	P values
AI Application Elements -> Supply Chain Agility	0.614	0.000
AI Application Elements -> Supply Chain Performance Outcomes	0.332	0.000
Supply Chain Agility -> Supply Chain Performance Outcomes	0.438	0.000

Table 7 presents the results of the direct relationships among the key constructs. The findings show that AI Application Elements have a strong positive effect on Supply Chain Agility ($\beta = 0.614$, $p < 0.001$) and a moderate positive effect on Supply Chain Performance Outcomes ($\beta = 0.332$, $p < 0.001$). Additionally, Supply Chain Agility significantly enhances Supply Chain Performance Outcomes ($\beta = 0.438$, $p < 0.001$). All relationships are statistically significant, indicating robust direct effects within the model.

Table 8. Indirect relationship

Indirect relationship	Path strength	P values
AI Application Elements -> Supply Chain Agility -> Supply Chain Performance Outcomes	0.269	0.000

Table 8 displays the result of the indirect relationship, indicating that AI Application Elements influence Supply Chain Performance Outcomes through the mediating effect of Supply Chain Agility. The indirect path shows a significant and positive effect ($\beta = 0.269$, $p < 0.001$), suggesting that Supply Chain Agility partially mediates the relationship between AI applications and performance outcomes.

4.2.2 R-square

The R^2 values were reported to assess the model's explanatory power. According to Cohen (1988), R^2 values of 0.26 to 0.50 indicate moderate predictive accuracy, while values above 0.50 reflect substantial predictive relevance.

Table 9. R-square

Endogenous constructs	R-square
Supply Chain Agility	0.377
Supply Chain Performance Outcomes	0.481

Table 9 presents the R-square (R^2) values, which indicate the model's explanatory power for the endogenous constructs. The R^2 value for Supply Chain Agility is 0.377, meaning that 37.7% of its variance is explained by AI Application Elements. The R^2 value for Supply Chain Performance Outcomes is 0.481, indicating that 48.1% of the variance is jointly explained by AI Application Elements and Supply Chain Agility. These values suggest moderate predictive power of the structural model (Cohen, 1988).

4.2.3 Effect Sizes (f^2)

The effect size (f^2) was evaluated to determine the relative contribution of each predictor to the variance explained in the endogenous constructs within the structural model. As proposed by Chin (1998), an f^2 value of 0.02 indicates a small effect, 0.15 represents a medium effect, and 0.35 reflects a large effect. These thresholds provide insight into the practical significance of each path relationship, beyond statistical significance alone, and help to identify the most influential variables in the model.

Table 10. f-square

Constructs	AI Application Elements	Supply Chain Agility	Supply Chain Performance Outcomes
AI Application Elements	-	0.605	0.133
Supply Chain Agility	-	-	0.230
Supply Chain Performance Outcomes	-	-	-

As shown in Table 10, AI Application Elements demonstrated a large effect on Supply Chain Agility ($f^2 = 0.605$), indicating a strong influence of AI on enhancing agility within the healthcare supply chain. In contrast, AI Application Elements exhibited a small effect on Supply Chain Performance Outcomes ($f^2 = 0.133$), suggesting a more modest direct contribution to performance metrics. Meanwhile, Supply Chain Agility showed a medium effect on Supply Chain Performance Outcomes ($f^2 = 0.230$), underscoring its critical role as a mediator that channels the benefits of AI applications into measurable performance improvements. These interpretations align with Chin's (1998) guidelines, where 0.02, 0.15, and 0.35 represent small, medium, and large effects,

4.2.4 Predictive Relevance

Predictive relevance (Q^2) was calculated using the blindfolding procedure to assess the model's predictive accuracy for out-of-sample observations. According to Chin (1998) and Hair et al. (2017), a Q^2 value greater than zero indicates that the model has predictive relevance for a specific endogenous construct.

Table 11. Construct Cross-Validated Redundancy (CCVR)

	SSO	SSE	Q ² (=1-SSE/SSO)
AI Application Elements	1990.000	1990.000	0.000
Supply Chain Agility	1194.000	842.224	0.295
Supply Chain Performance Outcomes	1592.000	1051.950	0.339

As shown in Table 11, the Construct Cross-Validated Redundancy (CCVR) results demonstrate that Supply Chain Agility ($Q^2 = 0.295$) and Supply Chain Performance Outcomes ($Q^2 = 0.339$) both have Q^2 values greater than zero. This confirms that the structural model has adequate predictive relevance for these endogenous constructs. Conversely, the Q^2 value for AI Application Elements is 0.000, which is expected, as it is an exogenous construct and thus not subject to predictive relevance testing. These findings suggest that the model is capable of accurately forecasting agility and performance outcomes in the healthcare supply chain context.

Table 12. Construct Cross-Validated Communalities (CCVM)

	SSO	SSE	Q ² (=1-SSE/SSO)
AI Application Elements	1990.000	960.290	0.517
Supply Chain Agility	1194.000	533.395	0.553
Supply Chain Performance Outcomes	1592.000	761.662	0.522

In addition, Construct Cross-Validated Communalities (CCVM) was used to examine the predictive accuracy of the measurement model. As shown in Table 12, all constructs exceed the threshold of zero for Q^2 , with values of 0.517 for AI Application Elements, 0.553 for Supply Chain Agility, and 0.522 for Supply Chain Performance Outcomes. These results provide strong evidence of communality prediction, indicating that the measurement model has substantial predictive relevance and that the observed indicators effectively explain the variance in their respective latent constructs.

Collectively, the CCVR and CCVM analyses reinforce the robustness of both the structural and measurement models, supporting their application in predicting healthcare supply chain agility and performance influenced by AI integration.

4.2.5 Level of Mediation Effect

Based on the results of the analysis of both direct and indirect relationships, the findings show that AI Application Elements have a positive and significant effect on Supply Chain Agility ($\beta = 0.614$, $p < 0.001$) and on Supply Chain Performance Outcomes ($\beta = 0.332$, $p < 0.001$). Additionally, Supply Chain Agility has a significant positive relationship with Supply Chain Performance Outcomes ($\beta = 0.438$, $p < 0.001$). The results also reveal a significant indirect effect, indicating that AI Application Elements influence Supply Chain Performance

Outcomes through the mediating role of Supply Chain Agility ($\beta = 0.269$, $p < 0.001$).

Since both the direct path (*AI Application Elements* → *Supply Chain Performance Outcomes*) and the indirect path (*AI Application Elements* → *Supply Chain Agility* → *Supply Chain Performance Outcomes*) are statistically significant, this indicates a partial mediation effect. According to Baron and Kenny (1986) and Hair et al. (2017), partial mediation is present when the mediator transmits part of the effect of the independent variable on the dependent variable, while the direct effect remains significant. Therefore, it can be concluded that Supply Chain Agility partially mediates the relationship between AI Application Elements and Supply Chain Performance Outcomes.

5. Conclusion

This study investigated the mediating role of supply chain agility in the relationship between artificial intelligence (AI) application and supply chain performance outcomes within Mubadala's healthcare sector in the UAE. Using a quantitative approach, data from 305 valid responses were analysed through Partial Least Squares Structural Equation Modelling (PLS-SEM) to validate the conceptual model. The measurement model assessment confirmed that all constructs were reliable and valid. The model demonstrated an adequate level of fit for further analysis, supporting its suitability for evaluating the relationships among AI application, supply chain agility, and performance outcomes.

In terms of structural results, AI Application Elements showed a strong positive effect on Supply Chain Agility ($\beta = 0.614$, $p < 0.001$) and a moderate positive effect on Supply Chain Performance Outcomes ($\beta = 0.332$, $p < 0.001$). Supply Chain Agility also significantly enhanced Supply Chain Performance Outcomes ($\beta = 0.438$, $p < 0.001$). Additionally, AI Application Elements had a significant indirect effect on performance outcomes through Supply Chain Agility ($\beta = 0.269$, $p < 0.001$), indicating a partial mediation effect. These results affirm the importance of AI in improving healthcare supply chains both directly and by enabling greater agility. The findings position Supply Chain Agility as a critical mechanism through which AI technologies enhance operational outcomes. The validated model provides practical insights for healthcare organizations seeking to integrate AI solutions to boost responsiveness, adaptability, and performance in dynamic operational contexts.

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