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Conceptual Model of the Smart Supply Chain in the Oil and Gas Industry in Line with the Fourth Industrial Revolution (National Iranian South Oil Company)

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A B S T R A C T

The objective of the present study is to propose a conceptual model for a smart supply chain in the oil and gas industry in alignment with the Fourth Industrial Revolution. The research method employed in this paper is descriptive-correlational, based on covariance matrix analysis, and conducted through a combination of library and field methods. The research model was derived through the analysis and interpretation of interviews conducted with experts in the country's oil and gas industry. Ultimately, using 318 questionnaires collected from the national oil and gas sector, a measurement and structural model was designed to assess the relationships among variables and to validate the developed model. According to the findings of structural equation modeling, in the National Iranian South Oil Company, "causal conditions influencing the implementation of the smart supply chain" affect the "phenomenon of smart supply chain implementation." The "phenomenon of smart supply chain implementation" affects "strategies for implementing the smart supply chain." "Contextual factors affecting strategies for implementing the smart supply chain" influence "strategies for implementing the smart supply chain." "Intervening conditions influencing strategies for implementing the smart supply chain" affect "strategies for implementing the smart supply chain." "Intervening conditions influencing strategies for implementing the smart supply chain" also affect the "phenomenon of smart supply chain implementation." Furthermore, "strategies for implementing the smart supply chain" impact the "outcomes resulting from smart supply chain implementation strategies." The results of the present study increase the awareness of researchers and stakeholders regarding smart supply chains in the oil and gas industry in the context of the Fourth Industrial Revolution and can be utilized by researchers and those interested in innovation within the oil and gas sector.

Keywords: *supply chain, smart supply chain, oil and gas industry, Fourth Industrial Revolution, National Iranian South Oil Company, structural equation modeling.*

1. Introduction

The Fourth Industrial Revolution has fundamentally transformed the logic of competition, operations, and value creation in global supply chains through the convergence of cyber–physical systems, the Internet of Things (IoT), artificial intelligence (AI), advanced analytics, and pervasive connectivity (Lasi et al., 2014; Saucedo-Martínez et al., 2018). In this new paradigm, supply chains are no longer linear and transaction-oriented; they are becoming interconnected, data-driven, and "smart," capable of sensing, predicting, and autonomously responding to environmental and market changes in real time (Nasiri et al., 2020; Zhang et al., 2023). For capital-intensive and risk-sensitive sectors such as oil and gas, which operate under high uncertainty, complex logistics, and stringent safety and environmental requirements, transitioning from traditional to smart supply chains is not merely a technological upgrade but a strategic imperative for long-term viability and competitiveness (Farahani et al., 2017; Ivanov, 2020).

Industry 4.0 provides the technological and conceptual foundation for this transformation by integrating digital technologies across the entire value chain—from upstream production to downstream distribution and customer service (Lasi et al., 2014; Papadopoulos et al., 2022). Smart factories, cyber–physical systems, and cloud-based platforms enable real-time monitoring, predictive maintenance, and advanced optimization of operations (Dong et al., 2021; Lee et al., 2019). Within this landscape, supply chain management is shifting towards digital and intelligent architectures that support dynamic coordination, end-to-end visibility, and autonomous decision-making, particularly in complex industrial ecosystems such as oil and gas, where disruptions can quickly propagate across global networks (Dolgui et al., 2020; Zouari et al., 2020).

The evolution of supply chains towards electronic, digital, and smart configurations has a substantial history. Early work on electronic supply chain management and multi-agent systems illustrated how digital connectivity can streamline coordination, information sharing, and decision support across organizational boundaries (Haitham, 2010). Subsequent studies emphasized supply chain agility, flexibility, and responsiveness as core strategic capabilities required to cope with volatile markets and technological turbulence (Fakoor Saghih, 2016; Karami et al., 2016). In industrial contexts, frameworks for digital supply chain management have been proposed to guide firms in redesigning processes, governance structures, and performance metrics to fully exploit digital technologies (Farahani et al., 2017; Kelly et al., 2020). These developments collectively point toward an emerging paradigm of intelligent or smart supply chains that combine connectivity, analytics, and automation to achieve superior performance.

Digitalization also reshapes the structure and capabilities of supply chain networks through advanced optimization and decision-support methods. Metaheuristic algorithms and fuzzy modeling have been used to design robust and efficient multi-stage supply chain networks under uncertainty, especially when demand is stochastic and capacity constraints are fuzzy (Khalifehzadeh & Fakhrzad, 2019). Cloud computing has been leveraged to provide scalable computational resources and shared platforms for collaborative planning and execution, enabling supply chain network configurations that are more flexible, cost-effective, and responsive to changing conditions (Hajipour & Rahbarjoo, 2019). These contributions highlight that smart supply chains are not only about adopting new technologies but also about reconfiguring network structures, processes, and decision rules in line with digital capabilities.

At the technological level, emerging and disruptive technologies—such as IoT, AI, blockchain, and advanced analytics—are key enablers of smart supply chains. IoT-based architectures provide continuous streams of data from assets, products, and infrastructure, enabling real-time tracking, monitoring, and control across the supply chain (Ben-Daya et al., 2019; Zhang & Sakurai, 2020). AI and machine learning allow firms to leverage these data for predictive analytics, anomaly detection, and decision automation, enhancing planning, risk management, and operational efficiency (Fosso Wamba et al., 2022; Ghodake et al., 2024). Blockchain and cyber–physical system architectures further contribute to trust, transparency, and secure data exchange in distributed supply chain ecosystems, which is particularly critical in high-stakes industries such as oil and gas (Lee et al., 2019; Zhang & Sakurai, 2020).

Recent advances have introduced integrated frameworks that combine AI and IoT (AIoT) to design sustainable smart supply chains, emphasizing not only efficiency and responsiveness but also environmental and social performance (Aliahmadi et al., 2022). Data-driven approaches using predictive analytics and machine learning have been shown to enhance the efficiency and reliability of supply chain management across different industries, suggesting substantial potential for their application in complex industrial supply chains (Ghodake et al., 2024). At the same time, research on disruptive innovation in the IT sector has introduced frameworks for identifying and evaluating the inter-company impacts of technological disruption, highlighting that digital and AI-based solutions can fundamentally reconfigure relationships, roles, and power dynamics within and across supply networks (Zeidanloo & Špaček, 2025). These insights are particularly relevant for large industrial enterprises navigating multi-actor ecosystems.

The literature on digital and smart supply chains also emphasizes new decision-making logics and partner selection mechanisms. Multi-criteria decision-making methods under fuzzy and hesitant linguistic environments have been applied to digital supply chain finance and partner selection, allowing firms to evaluate suppliers and financial partners based on complex, often qualitative criteria (Büyüközkan & Göçer, 2019; Liao et al., 2019). Digital supplier selection has been linked to enhanced supply chain quality management and improved firm performance, underlining the strategic role of digital sourcing decisions in building high-performing smart supply chains (Sharma & Joshi, 2020). In parallel, research has started to examine how data sharing, AI-based access control, and platform governance shape the functioning of "Agriculture 4.0" and other digitally intensive ecosystems, providing insights that are transferable to energy and industrial contexts (Spanaki et al., 2019).

From an operational perspective, the implications of Industry 4.0 for logistics, production planning, and tactical supply planning have been widely recognized. Studies on freight transportation and logistics highlight how emerging technologies affect capacity utilization, routing, and coordination in the digital era, emphasizing the need for new operational paradigms in logistics-intensive sectors (Dong et al., 2021). Smart manufacturing supply chains are increasingly modeled as integrated systems in which real-time information, automation, and advanced analytics support tactical supply planning and coordinated decision-making across multiple echelons (Oh & Jeong, 2019). Smart production systems and business process management frameworks propose drivers and structures to align digital technologies with process improvement and organizational learning, providing a foundation for designing smart supply chain strategies (Queiroz et al., 2020).

The COVID-19 pandemic and other disruptions have further accelerated interest in resilience and viability in digital and smart supply chains. Viable supply chain models that integrate agility, resilience, and sustainability perspectives demonstrate how firms can design networks capable of surviving and adapting to severe disruptions (Ivanov, 2020). Research on the interplay between the ripple effect and the bullwhip effect in supply chains shows that structural and operational dynamics are highly interdependent, especially under disturbance propagation (Dolgui et al., 2020). Digitalization and smart technologies have been proposed as key enablers of resilience, as they can enhance visibility, flexibility, and rapid reconfiguration capabilities; nonetheless, empirical evidence about how digitalizing the supply chain affects resilience remains emergent and context-dependent (Queiroz et al., 2019; Zouari et al., 2020).

Risk management and sustainability constitute additional pillars of smart supply chain research. Machine learning techniques have been used to predict supply chain risks, revealing trade-offs between model performance and interpretability that are highly relevant for managerial adoption in high-risk environments (Baryannis et al., 2019). Sustainability metrics are increasingly integrated into supply chain performance frameworks, such as extensions of the SCOR model, to capture social and environmental dimensions alongside economic ones (Stohler et al., 2018). In parallel, work on digital supply chain management across sectors—from video games to automotive—highlights the need to embed sustainability, transparency, and stakeholder value into digital transformation agendas, rather than treating digitalization as a purely efficiency-driven initiative (Farahani et al., 2017; Kelly et al., 2020).

Despite these advances, empirical understanding of smart supply chains in heavy and process industries—such as oil and gas—remains comparatively limited. Most existing studies focus on manufacturing, automotive, logistics, or consumer-oriented sectors, while the unique operational, safety, regulatory, and environmental conditions of oil and gas supply chains are rarely addressed in a comprehensive digital and smart supply chain framework (Nasiri et al., 2020; Zhang et al., 2023). Available studies on intelligent supply chains and digitalization provide conceptual and technical insights but often stop short of offering empirically validated, context-specific models that integrate causal conditions, contextual and intervening factors, implementation strategies, and multi-dimensional outcomes in a single coherent framework (Markalaei, 2016; Momeni & Qayoumi, 2017). The oil and gas industry, especially in emerging economies, thus constitutes a critical, yet underexplored, context for examining how smart supply chain concepts are operationalized and what drivers and consequences are most salient.

In response to this gap, recent research has begun to address how smart supply chain innovation models should be selected—whether exploitative or exploratory—depending on the strategic context and technological readiness of firms (Wei et al., 2023). Systematic reviews on digitalization and internationalization in small and medium-sized enterprises (SMEs) highlight the importance of alignment between digital capabilities, international strategy, and organizational resources (Bargoni et al., 2024). Moreover, studies on agile methodologies and product management in rapidly changing markets underscore the need for agility and iterative learning in implementing digital and data-driven initiatives, including those in supply chain contexts (Amajuoyi et al., 2024). At the relational level, evidence on supply chain partnerships, cross-functional integration, responsiveness, and resilience shows that collaborative structures are crucial for translating digital capabilities into sustainable competitive advantage (Badwan, 2024). Together, these contributions suggest that smart supply chain implementation in oil and gas must be analyzed not only as a technological project but also as an organizational, relational, and strategic transformation.

The notion of smart supply chains also intersects with broader debates on smart production systems, business process improvement, and future manufacturing paradigms. Studies have proposed frameworks for understanding how Industry 4.0 and digital supply chain capabilities create both challenges and opportunities for organizations, including issues of data governance, workforce skills, and organizational culture (Papadopoulos et al., 2022; Queiroz et al., 2019). Work on digital twins and real-time control in reverse supply chain operations illustrates how advanced modeling and simulation tools can support operational decision-making and closed-loop flows, with implications for circularity and sustainability in industrial ecosystems (Stuijt, 2021). In parallel, research on data sharing and AI-based access control decisions further indicates that governance mechanisms and trust architectures are central to realizing the potential of smart supply chains (Spanaki et al., 2019).

In the specific case of smart supply chain management in Industry 4.0, reviews and research agendas emphasize the need for integrative strategies that balance technological, organizational, and strategic considerations across regions and sectors (Zhang et al., 2023). Smart supply chain innovation models, combined with AIoT-based sustainable frameworks and digital partner selection techniques, provide a rich foundation for constructing context-sensitive conceptual models (Aliahmadi et al., 2022; Büyüközkan & Göçer, 2019; Wei et al., 2023). Nevertheless, there is still a lack of empirically grounded, indigenous models tailored to the structural characteristics, regulatory environments, and strategic priorities of national oil and gas industries. Given the sector's central role in economic development, energy security, and environmental sustainability, developing such a model is of both academic and practical significance.

Accordingly, the aim of this study is to develop and empirically validate an indigenous conceptual model of a smart supply chain for the oil and gas industry aligned with the Fourth Industrial Revolution, using structural equation modeling in the context of the National Iranian South Oil Company.

2. Methods and Materials

The research method used in this article is descriptive–correlational and employs covariance matrix analysis, conducted through a combination of library-based and field methods. Initially, a library review of the literature on the "smart supply chain of the oil and gas industry in alignment with the Fourth Industrial Revolution in the National Iranian South Oil Company," including the research background and existing theories on the subject, was performed. After identifying the indicators, a questionnaire was distributed among experts in the country's oil and gas industry, and the completed questionnaires were returned. Finally, using the structural equation modeling method, the proposed conceptual model of the study was analyzed.

To develop the conceptual model of the study, the literature was reviewed, and existing models in the field of the "smart supply chain of the oil and gas industry in alignment with the Fourth Industrial Revolution" were examined using keywords related to existing models in this domain. In the next step, in-depth interviews were conducted with experts in smart supply chains within the oil and gas industries of the country. In this regard, after extracting codes from the literature, interviews were conducted with experts to identify codes that may have been overlooked in the literature review. The components of the smart supply chain in the national oil and gas industries were extracted and presented in Table 1.

Table 1

Indigenous Model of the Smart Supply Chain in the Oil and Gas Industry

Criterion	Code	Indicator
Causal Conditions Influencing Smart Supply Chain Implementation (CC)	CC1	Environmental requirements of the oil and gas industry
	CC2	Smart technological advancements in oil and gas production
	CC3	Organizational motivations
Phenomenon of Smart Supply Chain Implementation (PH)	PH1	Smartization flow and process
	PH2	Smart variables
	PH3	Smart decision-making
Strategies for Implementing the Smart Supply Chain (ST)	ST1	Smart planning in the oil and gas industry
	ST2	Smart procurement in the oil and gas sector
	ST3	Smart oil and gas production
	ST4	Smart transportation of oil and gas
	ST5	Smart customer service and sales
	ST6	Smart after-sales services
Contextual Factors Affecting Smart Supply Chain Implementation Strategies (CO)	CO1	Challenges of the oil and gas industry
	CO2	Policies and regulations of the oil and gas sector
	CO3	National technological infrastructure
Intervening Conditions Affecting Smart Supply Chain Implementation Strategies (IN)	IN1	Corporate privacy
	IN2	Organizational culture
	IN3	Hardware and software infrastructures
	IN4	Human resource issues
Outcomes of Smart Supply Chain Implementation Strategies (OC)	OC1	Benefits of smart configuration
	OC2	Organizational improvement
	OC3	Supply chain quality enhancement
	OC4	Cost savings
	OC5	Delivery standardization
	OC6	Financial sustainability of the industry
	OC7	Environmental sustainability of the industry
	OC8	Social sustainability of the industry

To determine the sample size, Cochran's formula was used:

Formula 1)

$$n = (N \cdot (Z_{a}/_{2})^2 \cdot \delta^2) / (\varepsilon^2 (N - 1) + (Z_{a}/_{2})^2 \cdot \delta^2)$$

Where:

n = sample size

N = population size

δ = standard deviation of the variable proportion

ε = allowable error = 0.05

Z = standard normal variable corresponding to a 95% confidence level ($Z_{a}/_{2}$ = 1.96)

For a pilot sample of 30 participants, the standard deviation was estimated at 0.51418. Therefore, the sample size based on Cochran's formula is calculated as follows:

$$n = (1460 \times (1.96)^2 \times 0.51418) / ((1460 - 1) \times (0.05)^2 + (1.96)^2 \times 0.51418) = 317.99 \approx 318$$

Given the population size (1460 individuals), the sample size based on the finite population sampling formula was estimated at 318 participants. A simple random sampling method was used.

To assess the reliability of the measurement instrument, Cronbach's alpha was utilized. After distributing the pilot questionnaire, Cronbach's alpha results were obtained as shown in Table 2.

Table 2

Questionnaire Reliability

Dimension	Number of Variables	Cronbach's Alpha
Causal conditions influencing smart supply chain implementation	3	0.914
Phenomenon of smart supply chain implementation	3	0.918
Strategies for implementing the smart supply chain	6	0.871
Contextual factors affecting smart supply chain implementation strategies	3	0.831
Intervening conditions influencing smart supply chain implementation strategies	4	0.834
Outcomes of smart supply chain implementation strategies	8	0.847

Since all values exceed 0.70, the reliability of the questionnaire is confirmed, and the questionnaire was distributed for final completion across the entire National Iranian South Oil Company.

To assess the validity of the questionnaire, the "content validity" method was used. Content validity ensures that all dimensions and components capable of reflecting the intended concept are considered within the measurement. After developing the initial questionnaire framework, it was reviewed by 10 experts from the country's oil and gas industry, and its validity was confirmed.

3. Findings and Results

Inferential statistical techniques were used to analyze the data. After examining the normality of the distribution of the sample using the Kolmogorov–Smirnov (KS) test (via SPSS 20), structural equation modeling (via LISREL 8.80) was applied. First, for each dimension of the model, the relationship between subdimensions and latent variables was examined using confirmatory factor analysis in the form of measurement models. Then, the relationships among model dimensions were assessed within the structural model.

Based on the conceptual measurement model of the "smart supply chain of the oil and gas industry in alignment with the Fourth Industrial Revolution in the National Iranian South Oil Company," which illustrates the relationship between latent variables and observed variables, the following hypotheses were examined:

Hypothesis 1: In Iran's oil and gas industry, items CC1, CC2, and CC3 explain the latent variable "causal conditions influencing smart supply chain implementation."

Hypothesis 2: In Iran's oil and gas industry, items PH1, PH2, and PH3 explain the latent variable "phenomenon of smart supply chain implementation."

Hypothesis 3: In Iran's oil and gas industry, items ST1, ST2, ST3, ST4, ST5, and ST6 explain the latent variable "strategies for implementing the smart supply chain."

Hypothesis 4: In Iran's oil and gas industry, items CO1, CO2, and CO3 explain the latent variable "contextual factors influencing strategies for implementing the smart supply chain."

Hypothesis 5: In Iran's oil and gas industry, items IN1, IN2, IN3, and IN4 explain the latent variable "intervening conditions influencing strategies for implementing the smart supply chain."

Hypothesis 6: In Iran's oil and gas industry, items OC1, OC2, OC3, OC4, OC5, OC6, OC7, and OC8 explain the latent variable "outcomes of smart supply chain implementation strategies."

Based on the results of confirmatory factor analysis using LISREL 8.80, significant values were obtained as shown in Figures (1) through (6). As seen in Figures (1) through (6), all t-values related to the measurement model items were significant because their significance values exceeded 1.96. As a result, Hypotheses 1 through 6 are confirmed.

Figure 1

t-value model for "causal conditions influencing smart supply chain implementation"

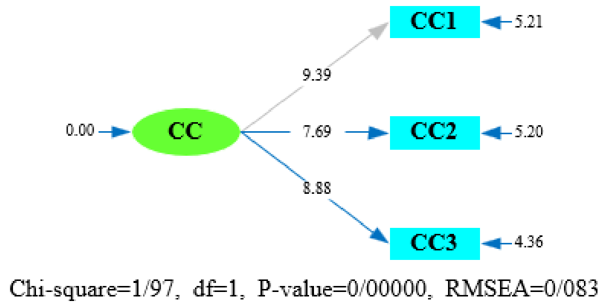


Figure 2

t-value model for "phenomenon of smart supply chain implementation"

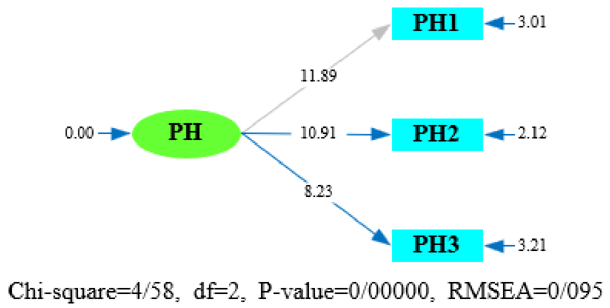


Figure 3

t-value model for "strategies for implementing the smart supply chain"

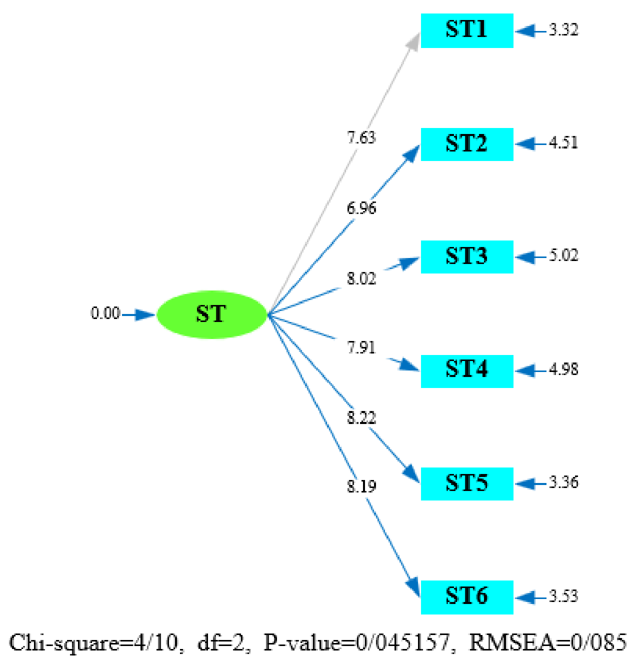


Figure 4

t-value model for "contextual factors influencing strategies for implementing the smart supply chain"

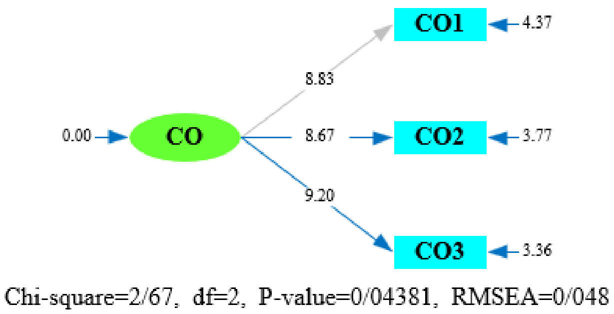


Figure 5

t-value model for "intervening conditions influencing strategies for implementing the smart supply chain"

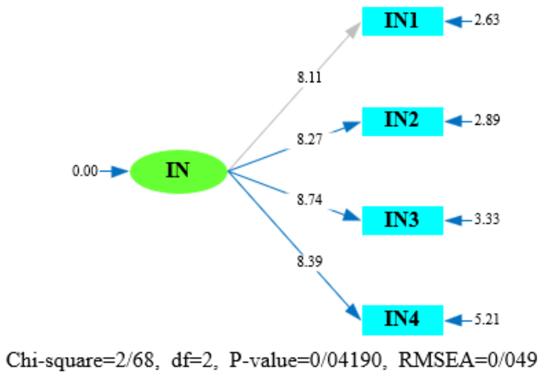
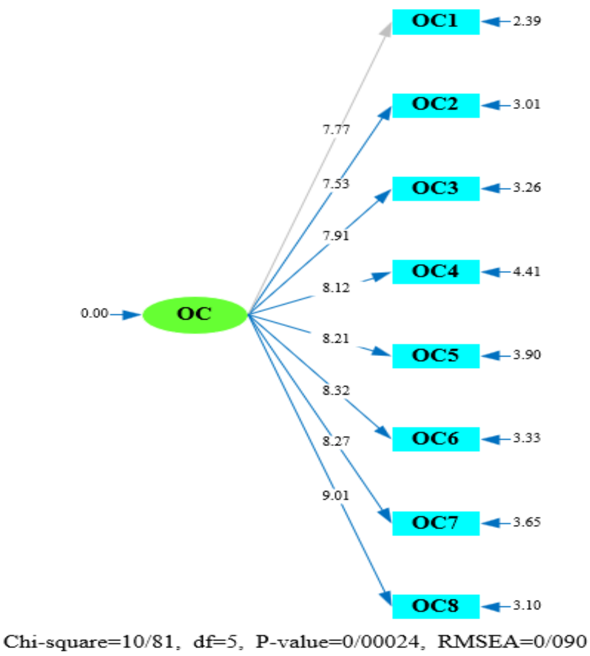


Figure 6

t-value model for "outcomes of smart supply chain implementation strategies"



Next, the standardized estimates of the components of the model are examined:

The standardized estimate model for the item "causal conditions influencing smart supply chain implementation" is shown in Figure (7).

Figure 7

Standardized estimate model for "causal conditions influencing smart supply chain implementation"

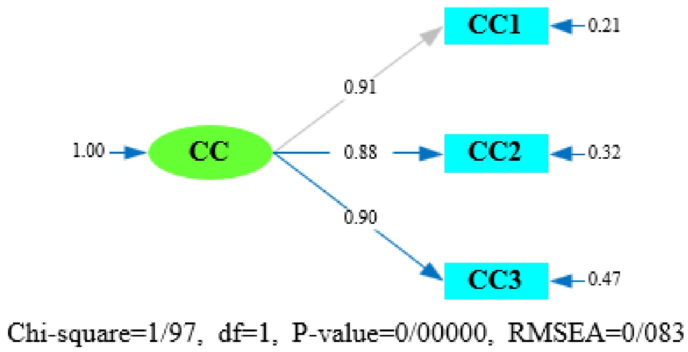


Figure (7) shows the degree to which each item explains the model, with the following priorities:

1. *Environmental requirements of the oil and gas industry (CC1)* with a factor loading of 0.91
2. *Organizational motivations (CC3)* with a factor loading of 0.90
3. *Smart technological advancements in oil and gas production (CC2)* with a factor loading of 0.88

The standardized estimate model for the item "phenomenon of smart supply chain implementation" is shown in Figure (8).

Figure 8

Standardized estimate model for "phenomenon of smart supply chain implementation"

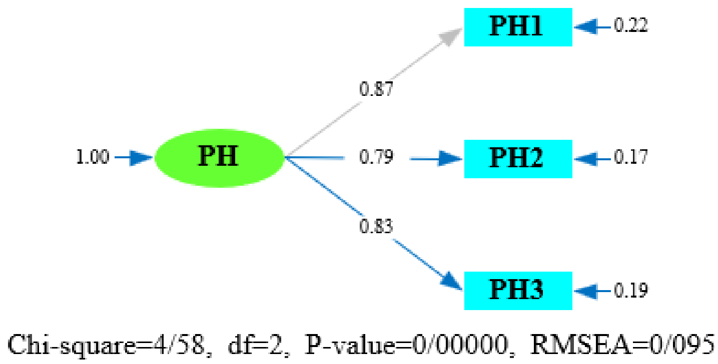


Figure (8) shows the degree to which each item explains the model, with the following priorities:

1. *Smartization flow and process (PH1)* with a factor loading of 0.87
2. *Smart decision-making (PH3)* with a factor loading of 0.83
3. *Smart variables (PH2)* with a factor loading of 0.79

The standardized estimate model for the item "strategies for implementing the smart supply chain" is shown in Figure (9).

Figure 9

Standardized estimate model for "strategies for implementing the smart supply chain"

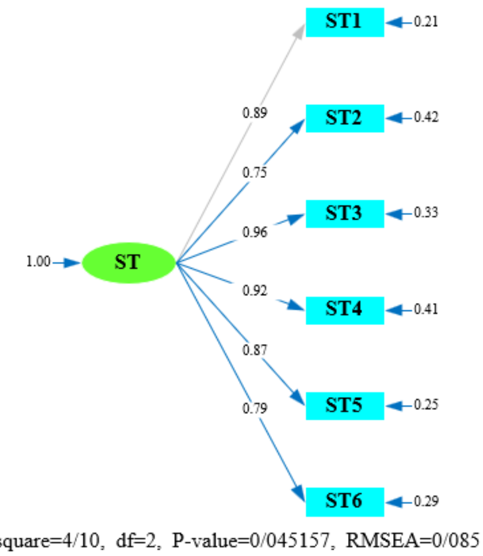


Figure (9) shows the degree to which each item explains the model, with the following priorities:

1. *Smart oil and gas production (ST3)* with a factor loading of 0.96
2. *Smart transportation of oil and gas (ST4)* with a factor loading of 0.92
3. *Smart planning in the oil and gas industry (ST1)* with a factor loading of 0.89
4. *Smart customer service and sales (ST5)* with a factor loading of 0.87
5. *Smart after-sales services (ST6)* with a factor loading of 0.79
6. *Smart procurement in the oil and gas sector (ST2)* with a factor loading of 0.75

The standardized estimate model for the item "contextual factors influencing strategies for implementing the smart supply chain" is shown in Figure (10).

Figure 10

Standardized estimate model for "contextual factors influencing strategies for implementing the smart supply chain"

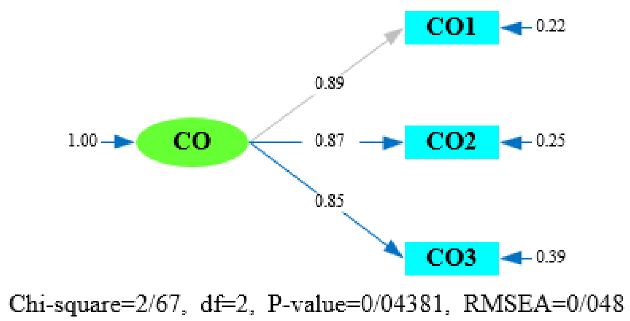


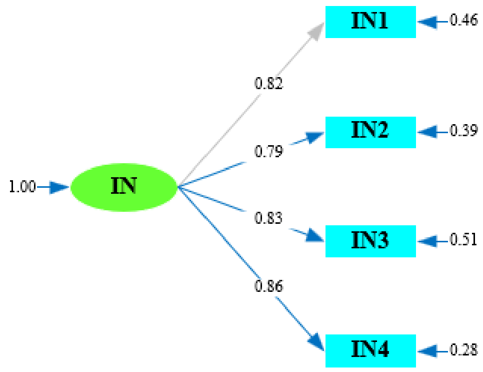
Figure (10) shows the degree to which each item explains the model, with the following priorities:

1. *Challenges of the oil and gas industry (CO1)* with a factor loading of 0.89
2. *Policies and regulations of the oil and gas sector (CO2)* with a factor loading of 0.87
3. *National technological infrastructure (CO3)* with a factor loading of 0.85

The standardized estimate model for the item "intervening conditions influencing strategies for implementing the smart supply chain" is shown in Figure (11).

Figure 11

Standardized estimate model for "intervening conditions influencing strategies for implementing the smart supply chain"



Chi-square=2/68, df=2, P-value=0/04190, RMSEA=0/049

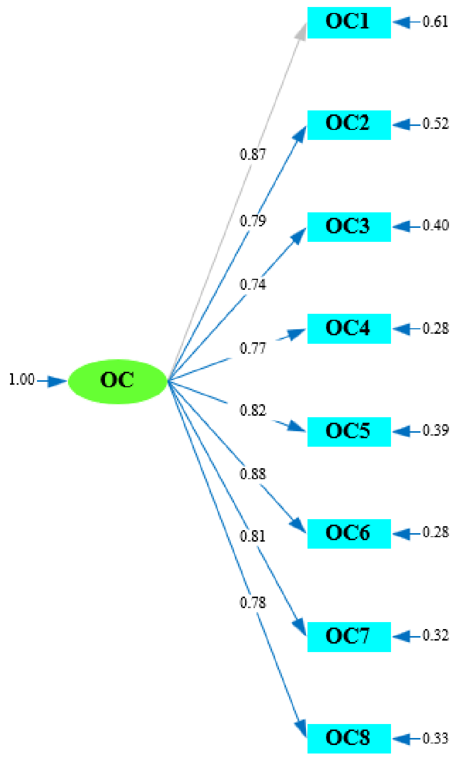
Figure (11) shows the degree to which each item explains the model, with the following priorities:

1. *Human resource issues (IN4)* with a factor loading of 0.86
2. *Hardware and software infrastructures (IN3)* with a factor loading of 0.83
3. *Corporate privacy (IN1)* with a factor loading of 0.82
4. *Organizational culture (IN2)* with a factor loading of 0.79

The standardized estimate model for the item "outcomes of smart supply chain implementation strategies" is shown in Figure (12).

Figure 12

Standardized estimate model for "outcomes of smart supply chain implementation strategies"



Chi-square=10/81, df=5, P-value=0/00024, RMSEA=0/090

Figure (12) shows the degree to which each item explains the model, with the following priorities:

1. *Financial sustainability of the industry (OC6)* with a factor loading of 0.88
2. *Benefits of smart configuration (OC1)* with a factor loading of 0.87
3. *Delivery standardization (OC5)* with a factor loading of 0.82
4. *Environmental sustainability of the industry (OC7)* with a factor loading of 0.81
5. *Organizational improvement (OC2)* with a factor loading of 0.79
6. *Social sustainability of the industry (OC8)* with a factor loading of 0.78
7. *Cost savings (OC4)* with a factor loading of 0.77
8. *Supply chain quality improvement (OC3)* with a factor loading of 0.74

4. Discussion and Conclusion

The purpose of this study was to develop and validate an indigenous conceptual model for smart supply chain implementation in the national oil and gas industry, specifically within the context of the National Iranian South Oil Company. The findings derived from structural equation modeling confirmed all six hypotheses and demonstrated that causal conditions, contextual factors, intervening conditions, implementation strategies, and outcome dimensions collectively form a coherent and empirically validated framework of a smart supply chain aligned with Industry 4.0 principles. The significance of these results lies not only in validating the measurement structure but also in illustrating how technological, organizational, and environmental conditions converge to shape smart supply chain transformation in a highly complex and technology-dependent industrial sector.

The first major finding showed that causal conditions—including environmental requirements, technological advancements, and organizational motivations—significantly explain the emergence of the smart supply chain implementation phenomenon. This aligns with studies emphasizing that Industry 4.0 adoption is driven by technological readiness, institutional pressures, and ecosystem-level changes (Lasi et al., 2014; Papadopoulos et al., 2022). Similar to the argument that energy-intensive and high-risk industries require strong digital infrastructures and regulatory alignment to adopt advanced supply chain technologies (Nasiri et al., 2020), our results indicate that environmental requirements—such as safety needs, geopolitical uncertainties, and operational risk management—serve as primary catalysts. This finding also echoes empirical work showing that technological advancements in AI, IoT, cyber–physical systems, and blockchain create foundational enablers for smart supply chain emergence (Ben-Daya et al., 2019; Lee et al., 2019; Zhang & Sakurai, 2020). Organizational motivations were also confirmed as strong drivers of transformation, consistent with the literature that highlights internal strategic ambitions, digital maturity, and competitive pressures as essential antecedents (Fakoor Saghih, 2016; Karami et al., 2016).

The second set of findings revealed that the phenomenon of smart supply chain implementation is most strongly explained by smartization processes, intelligent decision-making, and smart variables. This supports the growing consensus that smart supply chains must be built on continuous process digitalization, integration of sensing technologies, and real-time analytics (Zhang et al., 2023). The emphasis on intelligent decision-making aligns with studies showing that AI-embedded analytics improve supply chain quality, responsiveness, and resilience by enabling predictive insights and automated decisions (Fosso Wamba et al., 2022; Ghodake et al., 2024). Furthermore, the importance of smart variables—such as data granularity, connectivity, and adaptive algorithms—is consistent with models of Industry 4.0 that view data flows as the central nervous system of modern supply networks (Oh & Jeong, 2019; Sharma & Joshi, 2020).

The results concerning strategies for implementing smart supply chains revealed the highest factor loadings for smart production (ST3) and smart transportation (ST4). This finding confirms that the oil and gas sector, characterized by asset-intensive operations and geographically dispersed infrastructures, prioritizes operational digitalization in both production and logistics phases. This is strongly aligned with the literature emphasizing that IoT-enabled drilling, automated monitoring, and predictive maintenance are critical applications of Industry 4.0 in energy industries (Dong et al., 2021; Zouari et al., 2020). Smart transportation is similarly supported by previous analyses indicating that fleet digitalization, real-time tracking, and autonomous coordination improve safety, reduce costs, and enhance supply network flexibility (Dolgui et al., 2020; Nasiri et al., 2020). Smart planning (ST1), smart customer service (ST5), and smart after-sales services (ST6) also demonstrated strong explanatory power, reinforcing the view that full digital integration across the value chain is essential for strategic competitiveness (Queiroz et al., 2020; Wei et al., 2023). In contrast, smart procurement (ST2), although significant, showed comparatively lower factor loading, suggesting that the procurement function may still lag in digital adoption—an issue commonly observed in large industrial supply chains due to entrenched institutional routines and legacy systems (Hajipour & Rahbarjoo, 2019).

The findings for contextual factors indicated that industry challenges (CO1), followed by policies and regulations (CO2), and technological infrastructures (CO3), significantly influence strategy formulation. These results correspond with empirical studies showing that national digital infrastructure, regulatory environments, and institutional support are decisive for supply chain digitalization (Bargoni et al., 2024; Papadopoulos et al., 2022). Oil and gas industries globally operate under strict regulatory constraints and require continuous alignment with national legislation, environmental standards, and data governance policies. Similar to findings in smart manufacturing (Spanaki et al., 2019) and digital agriculture (Queiroz et al., 2019), this study's results confirm that contextual forces can either enable or constrain the digital transformation of supply networks.

Regarding intervening conditions, human resource issues emerged as the strongest factor, followed by hardware/software infrastructures, corporate privacy, and organizational culture. This aligns with research highlighting that digital transformation requires not only technological readiness but also workforce competencies, upskilling initiatives, and digital culture development (Amajuoyi et al., 2024; Stohler et al., 2018). Workforce-related constraints—particularly skills shortages, digital literacy gaps, and resistance to change—are repeatedly documented as major barriers to Industry 4.0 adoption (Nasiri et al., 2020; Papadopoulos et al., 2022). Privacy concerns, an increasingly critical issue in data-driven supply chains, reflect global debates on cybersecurity, trust, and data-sharing architectures (Lee et al., 2019; Spanaki et al., 2019). The importance of hardware and software infrastructures also mirrors existing work emphasizing that digital infrastructure maturity determines the pace and success of smart supply chain deployment (Karami et al., 2016; Oh & Jeong, 2019).

The final group of findings demonstrated that outcomes of smart supply chain implementation are most strongly associated with financial sustainability, smart configuration benefits, delivery standardization, and environmental sustainability. This is consistent with supply chain literature asserting that smart and digital supply chains improve cost structures, enhance asset utilization, strengthen risk mitigation, and contribute to environmental goals through optimized resource use (Baryannis et al., 2019; Ivanov, 2020). Financial sustainability emerged as the most influential outcome, underscoring the strategic value of digital transformation in high-cost industries such as oil and gas. Studies have similarly shown that efficient digital supply chains contribute to profitability, resilience, and long-term value creation (Badwan, 2024; Wei et al., 2023). Delivery standardization and quality improvements align with research emphasizing that digital supply chains enable real-time monitoring, standard-setting, and compliance enforcement across multiple tiers (Büyüközkan & Göçer, 2019; Liao et al., 2019). Environmental and social sustainability outcomes echo broader frameworks advocating for digitally enabled sustainable supply chain models (Aliahmadi et al., 2022; Stohler et al., 2018). These findings collectively demonstrate that successful implementation produces multi-dimensional improvements—not only technological and operational but also environmental, financial, and social.

Taken together, the results validate a comprehensive model that integrates dynamic causal relationships, contextual influences, organizational enablers, and strategic pathways for smart supply chain implementation in the oil and gas sector. This model aligns with current global research while also offering a context-specific contribution tailored to national industrial conditions.

The present study, although comprehensive, is subject to several limitations. First, the research was conducted within a single large national oil and gas company, which may limit the generalizability of findings to other sectors or smaller firms that operate under different technological, structural, and regulatory conditions. Second, the data were collected through self-report questionnaires and expert interviews, which could introduce response bias or subjective interpretation of constructs. Third, the cross-sectional design of the study restricts the ability to infer causality over time, and longitudinal changes in digital maturity or technological integration could not be captured. Fourth, the scope of the study focused primarily on internal organizational and technological dimensions and did not extensively incorporate external supply chain partners, global market dynamics, or geopolitical influences that significantly affect oil and gas supply chains. Finally, some emerging technologies—such as quantum computing, advanced digital twins, or autonomous robotic systems—were not fully integrated into the model due to limited adoption at the time of data collection.

Future research should consider conducting longitudinal studies to examine how smart supply chain capabilities evolve over time as digital technologies mature and organizational practices change. Comparative studies across multiple oil and gas companies, as well as cross-industry analyses, would help assess the generalizability of the conceptual model. Further research could incorporate external stakeholders, including suppliers, logistics partners, regulators, and global market actors, to capture the full ecosystem complexity of smart supply chains. Additionally, future studies could explore advanced theoretical frameworks such as dynamic capability theory, socio-technical systems theory, or platform ecosystem theory to deepen the conceptual understanding of digital transformation. More granular technological analyses—examining, for example, the integration of digital twins, blockchain–IoT hybrid architectures, or generative AI—could provide richer insight into the next frontier of smart supply chain innovation. Finally, future research should incorporate sustainability metrics and circular economy principles to understand how digitalization interacts with environmental and social objectives in the long term.

Organizations should invest in digital infrastructure, workforce upskilling, and cultural transformation to fully realize the benefits of smart supply chain implementation. Decision-makers should prioritize smart production and logistics capabilities, as these produced the strongest impacts in this study. Building collaborative networks and establishing clear data governance mechanisms will enhance trust and interoperability across supply chain partners. Policymakers should support digital adoption through regulations, incentives, and infrastructure investments. Managers should focus on strategically aligning technological initiatives with organizational goals while ensuring balanced attention to financial, environmental, and social sustainability outcomes.

Authors' Contributions

Authors contributed equally to this article.

Declaration

In order to correct and improve the academic writing of our paper, we have used the language model ChatGPT.

Transparency Statement

Data are available for research purposes upon reasonable request to the corresponding author.

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Declaration of Interest

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Ethics Considerations

In this research, ethical standards including obtaining informed consent, ensuring privacy and confidentiality were considered.

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