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Research Paper

AI-Driven Supply Chain Optimization: Structural Modeling of Key Factors Using ISM and MICMAC

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Abstract. Artificial Intelligence (AI) has emerged as a transformative enabler for supply chain optimization, offering advanced capabilities in predictive analytics, real-time decision-making, and operational efficiency. However, successful AI integration in supply chain management (SCM) is influenced by multiple interdependent technological, organizational, and governance-related factors. This study aims to identify and structure the key factors affecting AI-driven supply chain optimization in manufacturing industries. A mixed-methods approach was employed. In the qualitative phase, semi-structured interviews with domain experts were conducted to identify critical factors in AI adoption. These factors were then analyzed using Interpretive Structural Modeling (ISM) to develop a hierarchical model of relationships. Subsequently, MICMAC analysis was applied to classify factors based on their driving and dependence power. The results indicate that the technology deployment strategy, governance, compliance, and financial considerations are the most influential independent factors, serving as foundational drivers of AI adoption. Data and system requirements emerged as linkage factors with high driving and dependence power, while operational applications such as demand forecasting and automation were identified as dependent factors. The findings highlight the importance of structured AI strategies and robust data governance frameworks in achieving effective AI-driven supply chain transformation, providing valuable insights for practitioners and policymakers.

Keywords: Supply Chain Optimization, AI-driven Supply Chain, ISM, MICMAC Analysis, Data Governance.

Introduction

In today's globalized economy, businesses face increasingly complex supply chain challenges that hinder efficiency and responsiveness [1]. A lack of real-time visibility makes it difficult to monitor operations across multiple locations, leading to delays and inefficiencies. Inaccurate demand forecasting results in either overstocking or stockouts, directly impacting profitability. Additionally, logistical disruptions—driven by geopolitical tensions, environmental factors, and supplier dependencies—further destabilize supply chains. The integration of multiple stakeholders and technologies adds another layer of complexity, making coordination across the supply chain difficult [2]. These challenges highlight the

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urgent need for advanced, data-driven solutions to enhance decision-making and operational performance.

The evolution of supply chain management (SCM) has been shaped by technological advancements, with artificial intelligence (AI) playing a pivotal role in driving efficiency, reducing costs, and mitigating risks. In recent years, there has been a growing surge of expectations surrounding AI across various sectors, industries, and domains [3]. Since its initial introduction in the 1950s, AI's evolution has been marked by waves of excitement followed by phases of disillusionment [4]. From the early 2010s onward, particularly after the release of generative AI solutions like ChatGPT in late 2022, there has been a significant resurgence of interest from both researchers and practitioners [5]. AI-powered tools—such as predictive analytics and optimization algorithms—are transforming key areas including demand forecasting, inventory management, transportation logistics, and strategic decision-making [6].

Despite technological advancements, implementing AI in supply chain management continues to pose significant challenges. Current adoption remains largely experimental due to persistent technical and organizational barriers, as documented in recent industry surveys [7]. Fundamental obstacles include data quality and availability issues, with many organizations struggling with fragmented data systems and concerns about information security [8, 9]. The inter-organizational nature of supply chains further complicates data sharing, though emerging technological solutions such as federated learning have shown promise in addressing these challenges [10].

Technical integration presents another major hurdle, particularly when connecting AI systems with existing legacy infrastructure across organizational boundaries [11]. This requires careful attention to interoperability standards and cybersecurity measures [12, 13]. Financial considerations also play a critical role, as the substantial investments required to support infrastructure often outweigh the direct costs of AI implementation [14, 15].

Organizational factors equally influence successful adoption, particularly workforce capabilities and leadership engagement. The current shortage of technical talent with both AI expertise and supply chain domain knowledge creates significant implementation barriers [16, 17]. Furthermore, the opaque nature of many advanced AI models generates understandable concerns about reliability and accountability in decision-making processes [18]. These trust issues can be mitigated through approaches that emphasize model explainability and user involvement throughout development cycles [19].

While the path to widespread AI adoption in supply chains remains complex, strategic approaches that address these multidimensional challenges through technological innovation, organizational development, and gradual implementation show the most promise for successful transformation [20]. The current landscape suggests that realizing AI's full potential in supply chain management will require continued research and practical experimentation to overcome these persistent barriers.

AI-driven solutions offer predictive analytics, real-time insights, and intelligent decision-making, enabling firms to enhance operational efficiency, optimize inventory, and improve agility in dynamic market conditions [21]. Given the intricacies of SCM—which span sourcing raw materials to final product delivery—leveraging AI offers a significant opportunity to streamline operations and gain a competitive advantage. This paper explores AI-driven supply chain optimization using Interpretive

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Structural Modeling (ISM) to identify key factors and sub-factors. By examining AI's role in addressing supply chain challenges, we aim to provide insights into its strategic impact and practical applications.

1. Theoretical background and literature review

Iruku [22] demonstrated the application of Graph Neural Networks (GNNs) for modeling multi-tier supply chain structures, representing suppliers, manufacturers, and logistics hubs as nodes and their relationships as edges. By learning complex relational patterns and network dynamics, this approach enables earlier identification of emerging bottlenecks and systemic vulnerabilities, extending theoretical frameworks such as Resource Dependence Theory and Complex Adaptive Systems. On the other hand, Game Theory offers a strategic approach to decision-making by modeling interactions between supply chain stakeholders as competitive or cooperative games. This framework helps businesses predict stakeholder behavior, optimize pricing strategies, and foster collaboration while considering the actions and reactions of other participants [23]. Together, these theories provide a robust analytical foundation for optimizing supply chain operations in a highly interconnected and competitive global marketplace.

Amiri [24] reviewed the application of AI in agricultural supply chains and warehouse management, highlighting how machine learning and predictive analytics optimize inventory management, synchronize stock levels with consumption trends, and prevent overstocking and understocking. The study also emphasizes integrating robotics and automation to streamline operations and strengthen traceability across the supply chain. Moreover, AI is significantly reshaping SCM by streamlining processes, increasing operational efficiency, and lowering costs [25]. Shirafkana et al. [26] employed game theory to analyze strategic interactions among supply chain partners, including pricing, advertising, and subsidy decisions under volatile market conditions. Their findings highlight how competitive dynamics can be modeled to identify optimal strategies for manufacturers and retailers in blockchain-based supply chains. Qiu et al. [27] employed a Stackelberg game-theoretic framework to analyze strategic interactions among platforms, manufacturers, and retailers in e-commerce supply chains. Their findings demonstrate how contract formats (fixed-fee versus revenue-sharing) influence power distribution and coordination efficiency, highlighting the role of strategic alignment among supply chain partners in achieving optimal outcomes. Furthermore, Wang [28] proposed an integrated AI-enabled framework combining predictive modeling (LSTM networks for demand forecasting), prescriptive modeling (Reinforcement Learning for dynamic routing and inventory optimization), and collaborative decision-making to enhance efficiency in industrial supply chains. This holistic approach moves beyond isolated optimization methods to establish adaptive systems capable of continuous learning and improvement. Technologies such as machine learning (for demand forecasting and predictive maintenance), natural language processing (for analyzing unstructured customer data), and robotic process automation (for automating repetitive tasks) collectively enable businesses to streamline operations and maintain a competitive edge [29-31].

AI is significantly enhancing supply chain resilience by enabling businesses to adapt quickly to disruptions and dynamic market conditions. Through AI-powered technologies, companies can predict and manage risks such as supplier delays and transportation issues by analyzing historical data and risk indicators [32]. Garred et al. [33] proposed an automated framework for selecting demand forecast

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models that integrates a broad range of statistical and machine learning models with hyperparameter optimization. Validated on the M3 monthly dataset and in a real-world supply chain setting, their approach demonstrated significant improvements in forecast accuracy and provided an efficient decision-support system for managing complex, dynamic demand patterns. AI also optimizes production scheduling and capacity planning, reducing waste and minimizing production costs in manufacturing [34].

The literature underscores AI's transformative role in SCM, improving decision-making, sustainability, risk management, operational efficiency, and customer service. Patel [1] showed that AI enhances decision accuracy and speed, while Khan et al. [35] highlighted its sustainability benefits, reducing resource use and emissions. Kanti et al. [36] found that AI boosts risk prediction and logistics efficiency. Bibliometric analyses [37, 38] identify machine learning, NLP, and robotics as key AI technologies driving SCM transformation. However, challenges such as regulatory concerns, organizational readiness [39, 40], data privacy, and talent shortages [41, 42] remain significant barriers to successful adoption. While AI enhances efficiency, resilience, and sustainability, successful adoption requires addressing data integration, ethics, and regulations. Future research should focus on hybrid AI, workforce upskilling, and governance frameworks to maximize AI's SCM potential.

2. Methods

This research adopted a mixed-methods approach, integrating both qualitative and quantitative methods to provide a comprehensive understanding of AI-driven supply chain optimization. It followed a sequential exploratory design, where qualitative data were first collected and analyzed to identify key factors related to AI in supply chain optimization. Subsequently, a quantitative phase was conducted to further validate and explore the relationships among the identified factors using Interpretive Structural Modeling (ISM).

2.1. Expert Panel Composition

The sample consisted of 16 experts, including university professors (n=6) and managerial professionals (n=10) from manufacturing organizations. The purposive sampling strategy was guided by three inclusion criteria: (1) at least 10 years of professional or academic experience in supply chain management or industrial engineering; (2) active involvement in digital transformation or AI-related projects within the last five years; and (3) a publication or project record in the field of operations management. For university experts, additional criteria included holding a Ph.D. in a relevant field and having supervised at least 2 graduate theses in supply chain management or AI applications. To ensure diversity, we selected experts from six different manufacturing sub-sectors (automotive, electronics, pharmaceuticals, consumer goods, aerospace, and logistics). Table 1 summarizes the demographic profile and areas of expertise of the panel.

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Characteristic	Category	Frequency (N=16)
Affiliation	University (Professors)	6
	Industry (Managers/Directors)	10
Years of Experience	10–15 years	5
	16–20 years	7
	> 20 years	4
Industry Sub-sector	Automotive	3
	Electronics	3
	Pharmaceuticals	3
	Consumer Goods	3
	Aerospace	2
	Logistics	2
Area of Expertise	Strategic SCM / Planning	4
	Operations / Production	4
	IT / Digital Transformation	3
	Logistics / Distribution	3
	AI / Analytics	2

Table 1. Summary of Expert Panel Characteristics

Experts were identified through professional networks (e.g., LinkedIn, academic databases, and industry associations). Initial contact was made via email, followed by a formal invitation letter explaining the study objectives, the ISM methodology, and the expected time commitment (approximately 60–90 minutes for the interview and questionnaire completion). All participants provided informed consent prior to data collection.

The first step of the qualitative phase involved conducting an extensive literature review to establish a strong theoretical foundation for understanding AI in supply chain optimization. In the next stage of the qualitative phase, the semi-structured interviews were conducted with the selected experts. The interviews were designed to encourage open-ended responses, allowing the participants to share their insights and experiences regarding the application of AI in supply chain optimization. A carefully structured interview guide was developed, ensuring that all key research areas were covered while still allowing participants to discuss additional factors that may have emerged during the interview. The interviews were conducted in person and lasted 45-60 minutes. The conversations were audio-recorded with participants' consent and later transcribed verbatim to ensure accurate capture of their responses.

All completed questionnaires were screened for completeness. Responses with more than 10% missing data were excluded from the analysis. To assess the level of agreement among experts, Kendall's coefficient of concordance (W) was calculated. The obtained value ($W = 0.72$, $p < 0.05$) indicated acceptable consensus among the panel members, confirming the reliability of the collected judgments.

To enhance the validity of the findings, a pilot interview was conducted with one expert before the main data collection phase. A two-step process was also applied to ensure the reliability and validity of the qualitative findings. First, triangulation was employed by collecting data from a diverse group of experts with varying backgrounds, including both academic and industry professionals. This enabled a well-rounded understanding of the factors influencing AI integration in supply chains from multiple perspectives. Second, member checking was performed by sharing the transcribed interviews with the participants for confirmation.

DOI: 10.21791/IJEMS.2026.12

2.2. Thematic Analysis Process

After completing the interviews, the collected data were analyzed using thematic analysis. The analysis was conducted manually using a hybrid coding approach: an initial deductive codebook was developed based on the literature review, while inductive codes emerged from the interview data. Two researchers independently coded the first three transcripts to establish inter-coder reliability (agreement rate > 85%). The coding process involved systematically labeling meaningful segments of text, grouping similar codes into potential sub-themes, and subsequently aggregating them into broader main themes. All codes and themes were reviewed and refined through three iterative discussions among the research team. The identified themes were then categorized into main and sub-factors. The main factors were aligned with existing literature on AI in supply chain management, while the sub-factors were derived from the experts' direct experiences and insights. The outcome of the qualitative phase resulted in a comprehensive list of 8 main factors and 56 sub-factors. This final factor set is presented in Table 2.

Main Factor	**Sub-Factors**	***References***
Technology Deployment Strategy	— AI strategy definition — Resource allocation — AI integration framework — Timelines and milestones — Model selection and customization — Strategic alignment with business goals	*[1, 35]*
Governance, Compliance, & Financial Aspects	— Cost-benefit analysis — ROI evaluation — AI budgeting — Regulatory compliance — Data governance — AI legal considerations — Ethical guidelines for AI — Sustainability practices — AI impact auditing	*[23, 39, 40]*
Data and System Requirements	— Historical & real-time data integration — System scalability — Data availability — Data quality — Data security & privacy — Data interoperability across platforms — Data processing capacity	*[8, 26]*
Collaborative Ecosystem & Digital Networks	— Cross-organizational collaboration — Standardization of data — Process synchronization — Supplier & customer coordination	*[11,23,27]*

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Main Factor	**Sub-Factors**	***References***
	— Trust & transparency mechanisms — Digital supply chain platforms — Ecosystem-wide AI adoption	
Workforce and Organizational Adaptation	— Skill development — Employee AI adaptation — Change management strategies — Collaboration between AI systems & human workers — Overcoming resistance to AI adoption — Digital transformation culture — Technical expertise integration within teams	*[19,26,38]*
Risk Management & Decision Optimization	— AI for risk prediction — Contingency planning — Early warning systems — AI for crisis management — Scenario-based simulations — Real-time risk monitoring systems — AI-based predictive analytics for uncertainty management	*[6,27,36]*
Demand Forecasting & Inventory Management	— Predictive demand analytics — AI-driven demand sensing — Inventory optimization — Real-time inventory tracking — AI adaptability to market shifts — Use of external data sources (e.g., customer sentiment)	*[22,31,33]*
Supply Chain Operations & Automation	— AI in warehouse management — Robotics for order fulfillment — Route optimization — AI-based transportation management — Automated replenishment — AI for quality control — Integration with logistics networks	*[29,37,38]*

Table 2. Key factors and sub-factors in AI-driven supply chain optimization

After identifying 8 main factors and 56 sub-factors, the study proceeded to the quantitative phase. This phase aimed to explore the relationships between the identified factors using ISM. ISM is an interactive decision-making approach that is particularly well-suited for addressing complex issues. It structures various factors affecting a phenomenon, whether directly or indirectly —into a hierarchical model. This model helps rank and order these factors based on their relative importance, providing a clear

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understanding of their interrelationships. By employing ISM, the study aimed to identify and establish the influence of different factors involved in the digitalization of supply chains.

For this purpose, the same set of 16 experts who participated in the qualitative interviews were invited to complete the questionnaire. Their involvement ensured consistency and allowed the study to leverage both qualitative and quantitative data from the same knowledgeable pool of participants.

2.3. Conversion of Expert Opinions into Matrices

The experts participated in the survey to help define the relationships between the various factors. For each pair of factors (i, j), the experts were asked to indicate the direction of influence using the standard ISM notation: V (factor i influences j), A (factor j influences i), X (mutual influence), and O (no relationship). The majority rule (agreement by at least 10 out of 16 experts) was applied to determine the final relationship for each pair. Based on these aggregated pairwise judgments, we first constructed a Structural Self-Interaction Matrix (SSIM). The SSIM was then converted into an initial reachability matrix by assigning binary values to V, A, X, and O. Subsequently, the reachability matrix was checked for transitivity, and the transitive relationships were incorporated to derive the final reachability matrix. This approach enabled a clear depiction of the dependencies among the factors.

The study implemented rigorous validation measures to ensure data reliability. Subject-matter experts verified questionnaire content validity, while construct validity was confirmed through theoretical alignment of factor relationships. The ISM methodology followed a structured process: first developing a Structural Self-Interaction Matrix (SSIM), then converting it to a reachability matrix to examine factor relationships. Through matrix partitioning, hierarchical levels were established, enabling the construction of a digraph and final ISM model to visualize factor interdependencies. Complementary MICMAC analysis further evaluated each factor's driving power and dependence, providing critical insights for AI-driven supply chain optimization.

3. Results

To rank the factors influencing supply chain optimization, the main factors identified in Table 2 were utilized. After collecting expert responses, the aggregated responses were derived through mode analysis, ensuring that the final relationship structure reflected the most commonly agreed-upon expert opinions. This structured approach facilitated the systematic identification of direct and indirect influences among the factors, forming the basis for the subsequent analytical steps in the ISM approach. A contextual relationship of the “influence” type was established, indicating the directional impact between factors. This relationship was represented as follows: if factor *i* influences factor *j*, it was denoted with a specific symbol, ensuring clarity in hierarchical structuring.

To systematically capture these relationships, an SSIM was developed. This matrix was formulated based on expert assessments, reflecting the pairwise dependencies among factors. The assigned symbols in the SSIM were as follows: (1) “V” indicated that factor i influenced factor j; (2) “A” signified that factor j influenced factor i; (3) “X” represented a bidirectional influence between factors i and j; and (4) “O” signified no direct relationship between the two factors. This structured matrix formed the foundation for subsequent analytical steps in the ISM methodology. The SSIM is presented in Table 3.

DOI: 10.21791/IJEMS.2026.12

Factors	1	2	3	4	5	6	7	8
1. Technology Deployment Strategy	-	X	V	V	V	O	V	V
2. Governance, Compliance, and Financial Aspects		-	V	O	V	V	O	V
3. Data and System Requirements			-	V	O	A	V	O
4. Collaborative Ecosystem & Digital Networks				-	X	V	V	V
5. Workforce and Organizational Adaptation					-	V	O	V
6. Risk Management & Decision Optimization						-	X	O
7. Demand Forecasting & Inventory Management							-	V
8. Supply Chain Operations & Automation								-

Table 3. Results of SSIM Analysis

Next, all elements of the SSIM are replaced with binary values (i.e., 0 or 1) to generate the initial reachability matrix, presented in Table 4. This transformation follows the standard ISM procedure, where a value of 1 is assigned when factor i influences factor j, and 0 is assigned when no direct influence exists. To ensure that no information about the structural relationships is lost, the transitivity rule was applied: if factor A influences factor B, and factor B influences factor C, then factor A is considered to influence factor C, even if no direct relationship was originally identified by the experts. This step ensures that the binary recoding retains all indirect dependencies, and the resulting reachability matrix represents the full transitive closure of the original expert judgments. Therefore, while the binary format simplifies the relationships for mathematical processing, it preserves the essential dependency structure without discarding the indirect connections captured in the SSIM.

Factors	1	2	3	4	5	6	7	8
1. Technology Deployment Strategy	1	1	1	1	1	0	1	1
2. Governance, Compliance, and Financial Aspects	1	1	1	0	1	1	0	1
3. Data and System Requirements	0	0	1	1	0	0	1	0
4. Collaborative Ecosystem & Digital Networks	0	0	0	1	1	1	1	1
5. Workforce and Organizational Adaptation	0	0	0	1	1	1	0	1
6. Risk Management & Decision Optimization	0	0	1	0	0	1	1	0
7. Demand Forecasting & Inventory Management	0	0	0	0	0	1	1	1
8. Supply Chain Operations & Automation	0	0	0	0	0	0	0	1

Table 4. Results of the initial reachability matrix

Following this, the principle of transitivity is applied to ensure that indirect relationships between factors are captured as well. Transitivity, in the context of ISM, implies that if factor *i* influences factor *j* and factor j influences factor k, then factor i must also be considered to influence factor *k*. This principle ensures that all relevant relationships between factors are fully represented in the reachability matrix. As a result, the matrix is further updated to reflect these transitive relationships, yielding the final reachability matrix shown in Table 5.

Factors	1	2	3	4	5	6	7	8	Driver power
1. Technology Deployment Strategy	1	1	1	1	1	1	1	1	8
2. Governance, Compliance, and Financial Aspects	1	1	1	1	1	1	1	1	8
3. Data and System Requirements	0	0	1	1	1	1	1	1	6
4. Collaborative Ecosystem & Digital Networks	0	0	1	1	1	1	1	1	6
5. Workforce and Organizational Adaptation	0	0	1	1	1	1	1	1	6
6. Risk Management & Decision Optimization	0	0	1	1	0	1	1	1	5
7. Demand Forecasting & Inventory Management	0	0	1	0	0	1	1	1	4
8. Supply Chain Operations & Automation	0	0	0	0	0	0	0	1	1
Dependence	2	2	7	6	5	7	7	8	

Table 5. Results of the final reachability matrix

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This process systematically transforms the raw data collected from expert opinions into a structured matrix that captures both direct and indirect influences among the factors. The inclusion of transitivity ensures that the relationships are comprehensive and robust, paving the way for further analysis and the development of the ISM model. In the final stage of the analysis, the reachability matrix is used to determine the reachability set and antecedent set of each factor. A factor's reachability set includes the factor itself and any factors that it can influence. It consists of all the factors that have a value of "1" in the row of the factor under consideration. On the other hand, the antecedent set includes the factor itself and any factors that have the potential to influence it. This set is derived from the rows that contain a "1" in the column of the factor under examination.

Next, the intersection set for each factor is derived by comparing its antecedent set with its reachability set. The factors whose intersection set matches their reachability set are assigned to the first level. These factors are then removed from further iterations. The process of level partitioning is repeated until the levels for all factors are determined. This process of partitioning helps organize factors into a hierarchical structure based on their influence and dependence, as shown in Table 6. The factor that appears in the first level, which has the highest reachability and lowest dependency, is positioned at the top of the final ISM model.

Factors	Reachability set	Antecedent set	Intersection set	Level
Iteration 1				
F1	{1,2,3,4,5,6,7,8}	{1,2}	{1,2}	
F2	{1,2,3,4,5,6,7,8}	{1,2}	{1,2}	
F3	{3,4,5,6,7,8}	{1,2,3,4,5,6, 7}	{3,4,5,6,7}	
F4	{3,4,5,6,7,8}	{1,2,3,4,5,6}	{3,4,5,6}	
F5	{3,4,5,6,7,8}	{1,2,3,4,5}	{3,4,5}	
F6	{3,4,6,7,8}	{1,2,3,4,5,6,7}	{3,4,6,7}	
F7	{3,6,7,8}	{1,2,3,4,5,6,7}	{3,6,7}	
F8	{8}	{1,2,3,4,5,6,7,8}	{8}	I
Iteration 2				
F1	{1,2,3,4,5,6,7}	{1,2}	{1,2}	
F2	{1,2,3,4,5,6,7}	{1,2}	{1,2}	
F3	{3,4,5,6,7}	{1,2,3,4,5,6,7}	{3,4,5,6,7}	II
F4	{3,4,5,6,7}	{1,2,3,4,5,6}	{3,4,5,6}	
F5	{3,4,5,6,7}	{1,2,3,4,5}	{3,4,5}	
F6	{3,4,6,7}	{1,2,3,4,5,6,7}	{3,4,6,7}	II
F7	{3,6,7}	{1,2,3,4,5,6,7}	{3,6,7}	II
Iteration 3				
F1	{1,2,4,5}	{1,2}	{1,2}	
F2	{1,2,4,5}	{1,2}	{1,2}	
F4	{4,5}	{1,2,4,5}	{4,5}	III
F5	{4,5}	{1,2,4,5}	{4,5}	III
Iteration 4				
F1	{1,2}	{1,2}	{1,2}	IV
F2	{1,2}	{1,2}	{1,2}	IV

Table 6. Results of level partitioning of reachability matrix

Building upon the finalized reachability matrix and partitioned levels, the ISM model for the factors of AI-driven supply chain optimization was developed. In this step, the factors were arranged based on their hierarchical relationships, ensuring a clear representation of the identified dependencies. The hierarchical structure of the model illustrates the direction and strength of influence among the factors, providing insights into each factor's relative positioning and significance within the system. The final

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structured ISM model, which visually depicts the multi-level interdependencies among the factors, is presented in Figure 1. This model serves as a foundation for understanding how AI-related factors interact to drive supply chain optimization, offering a systematic framework for strategic decision-making and implementation.

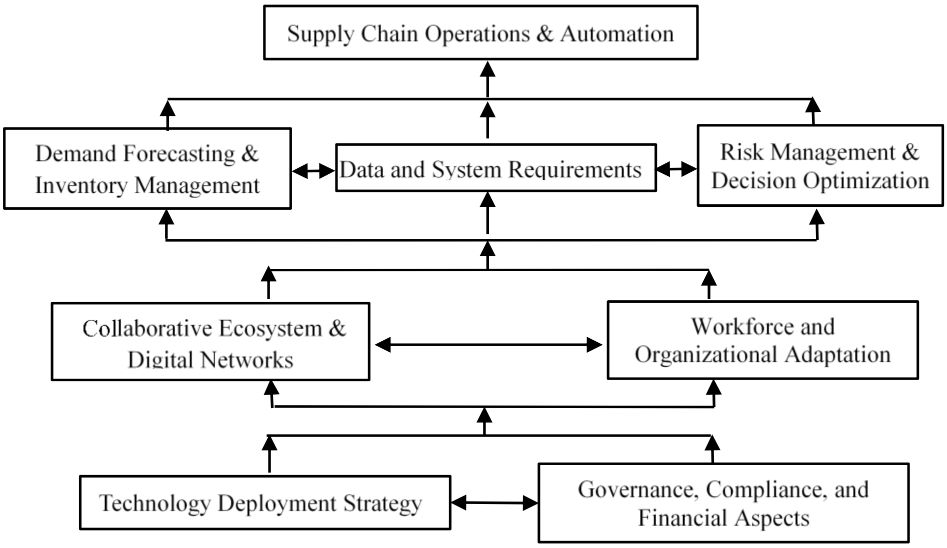

Figure 1. Hierarchical ISM model for AI-driven supply chain optimization factors

Finally, MICMAC analysis was conducted to evaluate the driving and dependence power of the factors influencing AI-driven supply chain optimization. This method helps categorize factors by their relative influence within the system. The driving power of a factor is determined by the total number of "1" entries in its corresponding row, while its dependence power is assessed by the total number of "1" entries in its column, as shown in Table 5.

Based on these values, the factors are classified into four distinct categories: (I) autonomous factors, which have low driving and dependence power and remain relatively disconnected from the system; (II) dependent factors, which exhibit weak driving power but strong dependence on other factors; (III) linkage factors, which possess both high driving and dependence power, making them highly sensitive to changes; and (IV) independent factors, which have strong driving power but low dependence, positioning them as key influencers in the system. The categorization of factors based on the MICMAC analysis is shown in Figure 2.

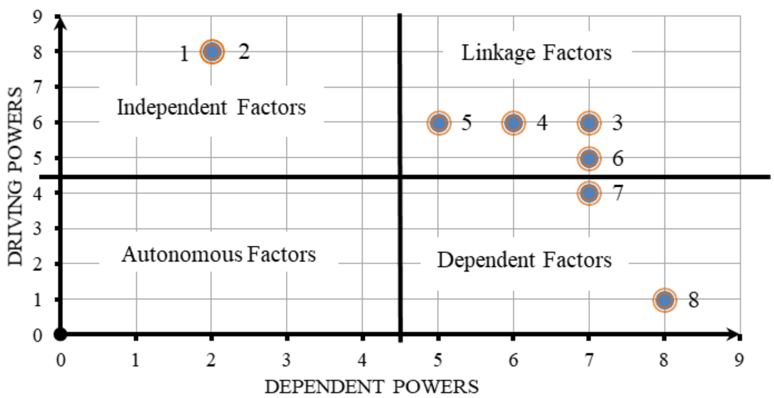

Figure 2. Categorization of factors based on MICMAC analysis

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4. Discussion and Concluding Remarks

This study systematically identifies and prioritizes critical success factors for AI-driven supply chain optimization using Interpretive Structural Modeling (ISM) and MICMAC analysis. The findings provide a structured framework for organizations to assess key drivers and dependencies, facilitating informed decision-making. Figure 2 reveals no autonomous factors, demonstrating complete interdependence among all elements in AI-driven supply chain optimization, necessitating holistic organizational approaches. The ISM model (Figure 1) identifies "technology deployment strategy" and "governance, compliance, and financial aspects" as foundational drivers with the strongest influence, confirmed by MICMAC analysis as independent variables.

These findings emphasize critical success factors: (1) technology deployment (clear strategy, resource allocation, integration framework, and business alignment) [1, 35] and (2) governance (cost-benefit analysis, regulatory compliance, ethical frameworks) [23, 39, 40]. Additional linkage factors include data/system requirements (historical/real-time data integration, scalability, security), collaborative ecosystems, organizational adaptation, and risk management. Data infrastructure quality proves particularly crucial for AI performance [8, 26], enabling predictive analytics and operational optimization. A collaborative ecosystem with digital networks is crucial for real-time supply chain coordination, requiring cross-organizational collaboration, data standardization, and process synchronization, enhancing transparency and resilience through AI-enabled platforms [11, 23, 27]. Successful AI implementation equally depends on organizational adaptation, including workforce upskilling, change management strategies, and overcoming resistance to digital transformation, supported by continuous training and cultural adaptation [19, 26, 38].

AI-driven decision optimization and risk management are critical for digital supply chains, enabling risk prediction, contingency planning, and real-time monitoring through scenario simulations and predictive analytics [6, 27, 36]. The ISM model's top level contains dependent factors: demand forecasting/inventory management and supply chain automation. AI-powered demand forecasting utilizes predictive analytics and external data to optimize inventory [22, 31, 33], while automation enhances efficiency in warehousing, logistics, and quality control [29, 37, 38].

This study demonstrates that manufacturing industries can leverage AI to optimize supply chains, enhancing productivity and reducing costs. Successful implementation requires a clear strategy encompassing defined objectives, resource allocation, and model selection, aligned with business goals while retaining market adaptability. Crucially, establishing robust data infrastructure with strong governance, standardized protocols, and cross-platform interoperability is fundamental for reliable AI decision-making, alongside rigorous data security measures. The research advocates a hybrid AI approach integrating machine learning, reinforcement learning, and evolutionary algorithms to create resilient supply chain solutions. Effective adoption further depends on cross-functional collaboration between technical and operational teams, coupled with comprehensive workforce training and change management initiatives to overcome implementation barriers.

Despite challenges such as data inconsistencies and skill gaps, strategic AI investment offers manufacturers a competitive advantage by improving efficiency, risk management, and supply chain resilience. By prioritizing data governance, advanced analytics, collaborative frameworks, and

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workforce development, firms can unlock significant operational value. A well-structured AI implementation strategy not only enhances current performance but also ensures long-term sustainability in an increasingly digital industrial landscape.

The findings are based on the judgments of 16 experts from manufacturing and academic backgrounds. While the panel was carefully selected, the results are sample-specific and may differ if applied to other expert groups, industries, or regions. Future research should validate the model across broader populations to enhance generalizability.

AI Use Statement

During the preparation of this manuscript, AI-assisted tools (including Grammarly and ChatGPT) were used solely for language editing and improving readability. No AI tools were used for data analysis, interpretation, figure preparation, or any other stage of the research process. The authors take full responsibility for the final content and integrity of the manuscript.

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Conflicts of Interest

The author declare no conflicts of interest.

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