

Role of AI in enabling supply chain 5.0 : Drivers, barriers and critical success factors

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Abstract

Supply Chain 5.0 combines advanced digital technologies with human-centric and sustainable operating principles, and Artificial Intelligence (AI) is central to this shift. This paper examines the drivers, barriers, and critical success factors (CSFs) shaping AI adoption in Supply Chain 5.0. Fifteen factors were identified through literature synthesis and expert consultation, and Interpretive Structural Modeling (ISM) combined with MICMAC analysis was used to establish their hierarchical and driving-dependence relationships. Results show that top management support and government policy are the strongest drivers, while implementation cost, workforce resistance, and integration complexity remain largely dependent outcomes. The resulting framework offers researchers, managers, and policymakers a structured basis for prioritising AI-adoption efforts in supply chain transformation.

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Keywords: *Artificial intelligence, Supply chain 5.0, Interpretive structural modelling, MICMAC analysis, Industry 5.0, Sustainable operations.*

1. Introduction

The transition from Industry 4.0 to Industry 5.0 is reshaping supply chain management by emphasising human-machine collaboration, resilience, and sustainability alongside digitalisation [11], [9]. Artificial

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Intelligence (AI) is a principal enabler of this transition, supporting real-time analytics, predictive decision-making, and intelligent automation across sourcing, production, and distribution [1], [2]. Within the theme of this conference on intelligent systems and their organisational impact, understanding how AI adoption is driven, constrained, and sustained in supply chains is directly relevant to both practice and policy.

While the operational benefits of AI in supply chains are well documented, organisations continue to face structural and behavioural obstacles to adoption, including data-related risks, workforce skill gaps, and high implementation costs [5], [4]. Existing studies tend to examine drivers, barriers, or success factors in isolation; comparatively few integrate all three into a single hierarchical model, and fewer still connect the resulting structure to an explicit theoretical lens. This paper addresses that gap by combining Interpretive Structural Modeling (ISM) with MICMAC analysis to build an integrated hierarchy of drivers, barriers, and critical success factors (CSFs) specific to Supply Chain 5.0, interpreted through the Technology-Organization-Environment (TOE) framework. This paper is guided by three research questions:

RQ1. What are the key drivers, barriers, and critical success factors of AI adoption in Supply Chain 5.0?

RQ2. How do these factors interrelate hierarchically to shape AI implementation outcomes?

RQ3. How can organisations prioritise and manage these factors to enable sustainable, human-centric Supply Chain 5.0 transformation?

2. Literature Review

Industry 5.0 extends Industry 4.0 by pairing digital and cyber-physical technologies with an explicit human-centric and sustainability agenda [12], [11]. Collaborative robotics, digital twins, and intelligent analytics are shown to reduce resource waste and improve operational resilience, provided organisations also invest in workforce upskilling and inclusive governance [9], [10]. This dual emphasis on technological capability and human wellbeing distinguishes Supply Chain 5.0 from earlier, efficiency-only digitalisation efforts. Continuous learning cultures further support the sustained development of digital competencies required for human-AI collaboration in supply chains [19].

Within this context, AI is reported to strengthen supply chain visibility, demand forecasting, and disruption response, with governance and leadership support repeatedly identified as preconditions for successful deployment [1], [2], [3]. At the same time, cross-sectoral studies find that data-privacy concerns, skill shortages, and integration difficulties with legacy systems constrain adoption, particularly for small and medium enterprises [5], [4], [7]. Emerging-economy studies further show that these barriers interact with regional policy environments, meaning the same driver can have different practical weight depending on institutional context [5]. Recent work on green supply chains in the FMCG sector similarly highlights that smart-technology adoption challenges—financial, technological, organisational and regulatory—directly shape sustainability outcomes, reinforcing the need for integrated analysis of drivers and barriers [20].

Compared with prior ISM-based studies of digital or AI adoption, which typically model either enablers or barriers, this paper's contribution is to integrate drivers, barriers, and CSFs within one hierarchy and to interpret the resulting structure through the TOE framework, allowing the technological, organisational, and environmental dimensions of AI adoption in Supply Chain 5.0 to be distinguished explicitly rather than treated as a single undifferentiated list of factors.

3. Theoretical Framework

This study is anchored in the Technology-Organization-Environment (TOE) framework, which explains technology adoption as a function of three contextual dimensions. The technological context (technology infrastructure readiness, integration complexity, interoperability) captures the digital capability required for AI deployment. The organisational context (top management support, workforce digital skill, resistance to change) reflects internal readiness and change-management capacity. The environmental context (government policy, competitive pressure, sustainability expectations) captures external forces that shape the pace and direction of adoption. Mapping the fifteen factors identified in Section 4.1 onto these three dimensions provides the theoretical basis for interpreting the ISM hierarchy in Section 5, and positions the study's contribution relative to prior, largely descriptive accounts of AI adoption in supply chains.

4. Methodology

This study combines a systematic literature review with expert-informed Interpretive Structural Modeling (ISM) and MICMAC analysis. Literature was drawn from academic databases (Scopus, ScienceDirect) to identify candidate factors and to ground the SSIM judgements described below [14], [15], [16]. A panel of twelve domain experts, comprising academics in supply chain and operations management and practitioners from manufacturing and logistics organisations, reviewed the candidate factor list and provided pairwise contextual-relationship judgements through structured consensus workshops; disagreements were resolved through discussion until majority agreement was reached. The resulting Structural Self-Interaction Matrix (SSIM) was converted into an Initial Reachability Matrix and, after applying transitivity, a Final Reachability Matrix, from which driving power, dependence power, and hierarchical levels were derived [17], [18]. The overall procedure is summarised in Figure 1.

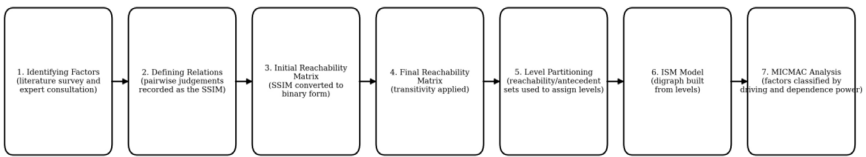


Figure 1
ISM-MICMAC procedure

(1) Identifying Factors – literature survey and expert consultation; (2) Defining Relations – pairwise judgements recorded as the SSIM; (3) Initial Reachability Matrix – SSIM converted to binary form; (4) Final Reachability Matrix – transitivity applied; (5) Level Partitioning – reachability/antecedent sets used to assign hierarchy levels; (6) ISM Model – digraph built from levels; (7) MICMAC Analysis – factors classified by driving and dependence power.

4.1 Identifying Factors

Fifteen factors were retained after synthesis and expert review, grouped as enablers (drivers), barriers, and critical success factors, summarised with their codes and definitions in Table 1.

Table 1
Enablers, Barriers and Critical Success Factors

Code	Factor	Meaning	Refs
D1	Top Management Support	Leadership commitment and strategic vision guiding AI-driven transformation.	[1], [5], [4]
D2	Technology Infrastructure Readiness	Digital platforms, IoT, cloud and data-sharing frameworks supporting AI integration.	[3], [2]
D3	Workforce Digital Skill Human-Robot Collaboration	Employee readiness to collaborate with AI and robotics.	[1], [9]
D4	Government Support Policy Framework	Regulations and incentives driving AI adoption.	[13], [8]
D5	Competitive Pressure Market Complexity	External market demands pushing adoption of AI for agility.	[6], [3]
D6	Supply Chain Visibility	Real-time data sharing and transparency across partners.	[1], [4]
D7	Sustainability Circular Economy Focus	Environmental and ethical emphasis on green logistics.	[9], [10]
B1	Data Privacy Cybersecurity	Risks from data exposure and interconnectivity in AI systems.	[5], [7], [3]
B2	Lack of Skilled Workforce	Shortage of professionals with AI and analytics skills.	[3], [1], [4]
B3	Resistance to Change	Organisational inertia against AI-enabled process change.	[1], [8]
B4	Integration Complexity	Difficulty aligning legacy systems with AI architectures.	[3], [2]
B5	High Implementation Cost	Substantial upfront and operating cost, notably for SMEs.	[8], [4]
CSF1	Strategic Alignment with Business Goals	AI initiatives tied directly to supply chain performance goals.	[1], [5], [4]
CSF2	Real-Time Decision-Making Capability	Predictive analytics enabling rapid response to disruption.	[1], [6]
CSF3	Collaborative Ecosystem Partner Readiness	Coordination among suppliers, logistics partners and stakeholders.	[2], [3]

Table 2
Structural Self-Interaction Matrix (SSIM)

[illegible][illegible]

After incorporating the transitivity principle, the Final Reachability Matrix was derived and is reported in Table 4. Interpretation of Table 4 shows that Top Management Support (D1) reaches nearly every other factor once indirect paths are included. D1 and D4 exhibit the highest driving power; the CSFs behave as dependent, outcome-level variables driven by the enabler set.

Table 4
Final Reachability Matrix (Transitivity Applied)

Factor	D1	D2	D3	D4	D5	D6	D7	B1	B2	B3	B4	B5	CSF1	CSF2	CSF3
D1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
D2	0	1	1	0	1	1	1	0	1	1	1	0	1	1	1
D3	0	0	1	0	0	1	1	0	1	1	1	0	1	1	1
D4	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1
D5	0	0	0	0	1	1	1	0	1	1	1	0	0	0	0
D6	0	0	0	0	0	1	1	0	0	0	0	0	1	1	1
D7	0	0	0	0	0	0	1	1	0	0	0	1	1	1	1
B1	0	0	0	0	0	0	0	1	0	0	0	0	0	1	1
B2	0	0	0	0	0	0	0	1	1	1	0	1	1	1	1
B3	0	0	0	0	0	0	0	0	0	1	0	0	1	1	1
B4	0	0	0	0	0	0	0	0	0	1	1	0	0	1	1
B5	0	0	0	0	0	0	0	1	0	1	0	0	0	1	1
CSF1	0	0	0	0	1	0	0	0	0	0	0	0	1	1	1
CSF2	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1
CSF3	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1

Table 5 summarises the driving power, dependence power, hierarchical level and MICMAC classification for each factor.

Table 5
Driving Power, Dependence Power, Level and MICMAC Classification

Code	Factor	Driving Power	Dependence Power	Level	MICMAC Class
D1	Top Management Support	15	7	4	Driver
D2	Technology Infrastructure	11	8	3	Linkage
D3	Workforce Digital Skill	11	9	3	Linkage
D4	Government Support Policy	15	10	2	Linkage

Contd...

D5	Competitive Pressure	7	9	1	Dependent
D6	Supply Chain Visibility	7	7	1	Autonomous
D7	Sustainability Focus	9	8	2	Linkage
B1	Data Privacy Cybersecurity	3	6	1	Autonomous
B2	Lack of Skilled Workforce	8	9	2	Linkage
B3	Resistance to Change	7	9	1	Dependent
B4	Integration Complexity	7	8	1	Dependent
B5	High Implementation Cost	6	8	1	Dependent
CSF1	Strategic Alignment	7	7	1	Autonomous
CSF2	Real-Time Decision Making	7	9	1	Dependent
CSF3	Collaborative Ecosystem	2	12	1	Dependent

5. Results and Discussion

In the Figure 3, level partitioning places D1 (Top Management Support) alone at Level 4, the most independent position in the hierarchy; D2 (Technology Infrastructure) and D3 (Workforce Digital Skill) at Level 3; D4 (Government Support Policy), D7 (Sustainability Focus) and B2 (Lack of Skilled Workforce) at Level 2; and the remaining factors (D5, D6, B1, B3, B4, B5, CSF1, CSF2, CSF3) at Level 1, the most dependent position (see Table 5).

In Figure 2, the Driver quadrant contains D1 (Top Management Support), which shows the highest driving power and comparatively low dependence, confirming leadership commitment as the root enabler of AI adoption. The Linkage quadrant contains D2 (Technology Infrastructure), D3 (Workforce Digital Skill), D4 (Government Support Policy), D7 (Sustainability Focus), and B2 (Lack of Skilled Workforce); these factors both influence and are influenced by the wider system, so interventions here tend to produce system-wide effects. The Autonomous quadrant (B1 Data Privacy Cybersecurity, CSF1 Strategic Alignment, D6 Supply Chain Visibility) shows comparatively localised influence. The Dependent quadrant (D5, B3, B4, B5, CSF2, CSF3) is shaped by upstream drivers and linkages rather than driving the system itself, indicating that these outcomes improve as a consequence of action on the Driver and Linkage factors rather than through direct intervention.

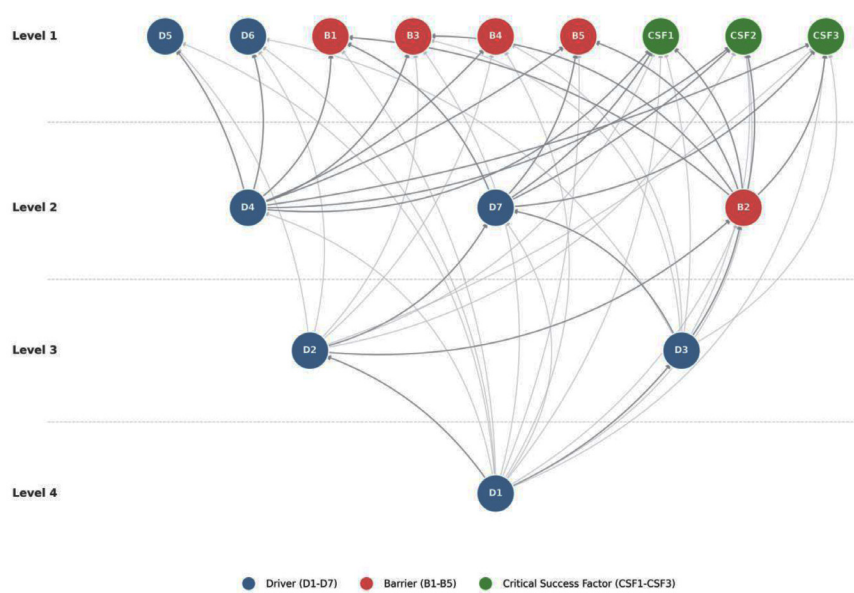


Figure 2

ISM-Based Hierarchical Digraph of Drivers, Barriers, and CSFs

Arrows indicate directional influence from lower- to higher-level factors, consistent with the level partitioning in Table 5 and the Final Reachability Matrix in Table 4. D1 (Top Management Support) occupies Level 4 as the root driver; D5, D6, and the barrier/CSF factors occupy Level 1 as the most dependent outcomes.

Managerial takeaways:

- (1) Prioritise top-management sponsorship and a clear AI governance mandate before large-scale technology investment.
- (2) Treat technology infrastructure and workforce upskilling as joint, not sequential, investments, since both sit in the Linkage quadrant.
- (3) Expect cost, resistance, and integration barriers to ease as driver and linkage factors mature, rather than requiring separate large-scale interventions.
- (4) Use government policy signals as an external lever to justify and accelerate internal AI investment cases.

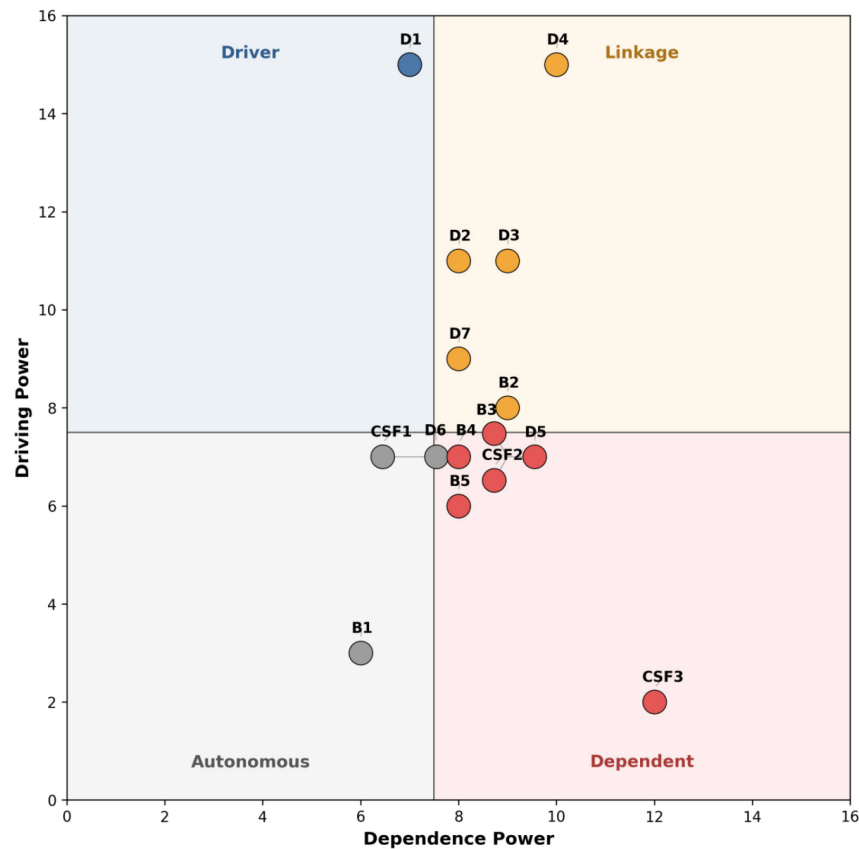


Figure 3
MICMAC Driving Power-Dependence Power Analysis

Quadrant boundaries are set at half the maximum possible power (7.5) for the fifteen-factor matrix. Point placement and classification correspond to the driving power, dependence power, and MICMAC class reported in Table 5.

6. Contributions

Theoretical contribution: this paper integrates drivers, barriers, and CSFs of AI adoption within a single ISM-MICMAC hierarchy and interprets that hierarchy through the TOE framework, extending prior single-dimension ISM studies of digital supply chain adoption.

Managerial contribution: the classification of factors into driver, linkage, autonomous, and dependent categories offers a prioritisation tool for supply chain and technology leaders deciding where to direct limited

AI-adoption resources, and a diagnostic reference for policymakers designing supporting regulation.

7. Limitations

The ISM/MICMAC approach relies on expert judgement, which may introduce subjectivity into the SSIM and consequent level assignment. The twelve-expert panel, while diverse across academia and industry, may not capture all sector-specific or regional variation, limiting generalisability. AI-adoption practice is also evolving quickly, so specific factor relationships may shift and warrant periodic re-validation.

8. Future Research Directions

Future work should validate the proposed hierarchy with larger, cross-sector and cross-regional samples, ideally using longitudinal data to observe how factor relationships evolve. Comparative studies of region-specific regulatory frameworks would clarify how the environmental (TOE) dimension varies across markets. Extending the model to account for emerging technologies such as generative AI and edge computing would also be a useful direction.

9. Conclusion

This study shows that AI adoption in Supply Chain 5.0 is not the product of isolated technology investment but of a layered structure in which top management commitment and government policy act as root drivers, technology infrastructure and workforce skills act as central linkages, and cost, resistance, and integration barriers remain largely dependent outcomes. Addressing the driver and linkage factors first, rather than tackling barriers directly, offers organisations a more efficient path toward sustainable, human-centred AI adoption in supply chain operations.

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