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RESEARCH PAPER

Evaluating SC 5.0 preparedness through human–AI collaboration and digital maturity in indian capital-intensive PSUS

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ABSTRACT

Purpose: This study aims to develop and empirically validate a hybrid multi-method framework to assess Supply Chain 5.0 (SC 5.0) preparedness in India's capital-intensive engineering Public Sector Undertakings (PSUs). The framework evaluates readiness across five dimensions: Technological Readiness, Leadership & Change Management, Human–AI Collaboration Capability, Workforce Digital Skills and AI Literacy, and Organizational Learning & Innovation.

Methodology: A quantitative research design was employed using primary survey data from 485 professionals across six capital-intensive PSUs. The analysis was conducted in three phases: (i) Structural Equation Modeling (SEM) to test causal relationships and validate hypotheses, (ii) Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) to construct a SC5.0 Readiness Index and rank PSUs, and (iii) Artificial Neural Networks (ANN) to predict and cross-validate the robustness of readiness drivers.

Findings: SEM results reveal that Technological Readiness ($\beta = 0.331$, $p < 0.01$), Workforce Skills ($\beta = 0.298$, $p < 0.01$), and Human–AI Collaboration Capability ($\beta = 0.279$, $p < 0.01$) significantly influence SC 5.0 readiness, with leadership commitment moderating the impact of digital infrastructure on transformation outcomes ($p < 0.05$). TOPSIS highlights BHEL (0.741), NTPC (0.703), and GAIL (0.689) as top-performing PSUs, while ANN validation achieved 91.48% accuracy, confirming model robustness.

Research Implications: The study advances theoretical understanding by integrating structural modelling with machine learning-based predictive analytics, offering a holistic approach to assessing SC 5.0 readiness. The high predictive accuracy of the ANN model ($R^2 = 0.8841$; equivalent to 91.48% accuracy) underscores the robustness of the framework, demonstrating that leadership, agility, and change-handling dynamics can be reliably forecast as critical enablers of SC 5.0. This establishes a methodological precedent for combining causal, prescriptive, and predictive approaches in future supply chain transformation research.

Practical & Social Implications: The findings provide actionable insights for PSU managers and policymakers to enhance digital transformation, workforce upskilling, and human–AI collaboration, thereby improving operational resilience and supporting sustainable industrial growth.

Keywords: Supply Chain 5.0; Indian PSUs; Technological Readiness; Human-AI Collaboration; SEM-MCDM-ANN; Readiness Index; Digital Transformation; Public Sector Benchmarking.

1 INTRODUCTION

The modern global supply chain landscape is witnessing a pivotal transition toward Supply Chain 5.0 (SC 5.0)—a paradigm that synergizes human-centric design with advanced digital technologies such as artificial intelligence (AI), the Internet of Things (IoT), blockchain, and robotic process automation. Distinct from its predecessor Industry 4.0, SC 5.0 emphasizes

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collaborative intelligence, resilience, and responsible automation, redefining how organizations navigate disruptions, stakeholder expectations, and sustainability demands (Yaroson *et al.*, 2025; Smith, 2024). Despite notable advancements in digital infrastructure, Indian capital-intensive Public Sector Units (PSUs)—particularly those in core engineering sectors—continue to struggle with fragmented SC 5.0 implementation. As noted by De Vass *et al.* (2021), the infusion of automation and IoT has transformed supply chains globally. Yet, within Indian PSUs, there remains no validated framework for measuring SC 5.0 preparedness, resulting in policy inertia, poor benchmarking, and delayed innovation cycles. Moreover, there is a lack of predictive models or multidimensional metrics to assess readiness across key enablers such as technology integration, workforce digital literacy, and organizational adaptability.

The first strategic driver of SC 5.0 is Technological Readiness, encompassing AI, ERP, IoT, and blockchain. AI can automate decision-making, enhance predictive analytics, and improve real-time operations by Helo & Hao (2022), while ERP systems ensure digital integration and performance optimization. Blockchain adds transparency and decentralization in high-stakes supply chain processes. However, such technologies can only succeed if embedded within a visionary leadership ecosystem. Leadership and Change Management remain crucial in enabling large public systems to adapt. Strong, crisis-resilient governance has been repeatedly linked to effective supply chain outcomes, especially in emergency response. However, Indian PSUs often lack change-ready leadership structures that can drive digital transformation and organizational agility. A core innovation of SC 5.0 is the capacity for Human–AI Collaboration, wherein machine intelligence augments human judgment, rather than replacing it. As described by Smith (2024) and Mehmood (2022), such collaboration requires robust human–AI trust, ethical design, and real-time interpretability. Leading firms such as Amazon and UPS are leveraging AI-powered systems for dynamic inventory and logistics optimization (Richey Jr. *et al.*, 2023). However, Indian PSUs face systemic constraints in aligning such capabilities with legacy systems. Another critical enabler is Workforce Skills and AI Literacy. The success of SC 5.0 depends on a digitally fluent workforce capable of engaging with ERP systems, predictive algorithms, and collaborative tools. Wahab *et al.* (2024) underscore the importance of hybrid skill development—combining technical, cognitive, and emotional intelligence—especially in digitally transitioning supply chains. In regions like Indonesia, digital resistance in logistics-heavy supply chains has shown that AI literacy must be paired with business-specific digital learning strategies. Organizational Learning and Innovation are the cement that holds digital infrastructure together with operational excellence. Research by Eryarsoy *et al.* (2022) is evidence that organizational innovativeness, when combined with systematic learning environments, has a profound effect on improving adaptability and supply chain resilience. Gupta *et al.* (2020) also contend that companies need to create systematic approaches to overcome innovation challenges like risk aversion, conventionalism, and R&D underinvestment—hurdles more common in public sector entities.

Table 1 shows an integrated analytic framework summarizing the study's research questions (RQs), objectives (ROs), and testable hypotheses (Hs) in a traceable and structured manner. This triadic alignment is crucial for conceptual clarity and methodological validity, providing a clear roadmap for the next steps of empirical analysis. The architecture is based on five foundational dimensions of SC 5.0 readiness—Technological Readiness, Leadership and Change Management, Human-AI Collaboration Capability, Workforce Skills & AI Literacy, and Organizational Learning & Innovation—each critically based on existing literature and tested using theoretical frameworks. By integrating literature synthesis, empirical validation, and policy alignment, this research contributes meaningfully to the theory, practice, and governance of digital transformation in one of India's most strategically vital sectors. Specifically, it offers actionable insights for managers, technologists, and public policymakers working to unlock the value of Supply Chain 5.0 (SC 5.0) through intelligent automation, human-machine collaboration, and innovation-centric organizational culture.

Table 1 - Integrated Framework of Research Questions, Objectives, and Hypotheses

Research Question (RQ)	Corresponding Research Objective (RO)	Testable Hypothesis (H)
RQ1: What is the current state of digital and organizational preparedness for SC 5.0 in Indian PSUs?	RO1: To conceptualize a multidimensional model to assess the SC 5.0 preparedness of Indian capital-intensive PSUs.	H1: Technological readiness positively influences overall SC 5.0 preparedness.

RQ2: Which factors most significantly influence SC 5.0 readiness in these units?	RO2: To develop and validate a hybrid SEM–MCDM framework to analyze readiness factors.	H2: Leadership commitment significantly moderates SC 5.0 adoption outcomes. H3: Workforce digital skills and AI literacy are strong predictors of SC 5.0 readiness.
RQ3: How do Indian PSUs compare in their SC 5.0 adoption journey?	RO3: To build a SC 5.0 Readiness Index for PSU benchmarking.	(Not directly linked to a testable hypothesis; outcome driven through MCDM index.)
RQ4: What are the perceived challenges and enablers in transitioning to SC 5.0?	RO4: To identify strategic and organizational barriers to SC 5.0 transformation. RO5: To recommend a policy-oriented roadmap for enabling SC 5.0 transition in Indian PSUs.	H4: Human-AI collaboration capability has a significant effect on operational agility. H5: Organizational learning culture mediates the relationship between digital infrastructure and SC 5.0 implementation.

Despite the growing strategic importance of these five dimensions, no prior comprehensive or empirically validated framework exists to benchmark the SC 5.0 readiness of Indian capital-intensive PSUs. Addressing this research void, the present study proposes and operationalizes a hybrid SEM–MCDM–ANN-based readiness assessment model, uniquely tailored for the operational realities, governance constraints, and digital ambitions of public sector engineering enterprises in India. The table thus serves as both a conceptual scaffold and a practical blueprint for guiding the research process, hypothesis testing, and policy formulation.

2 LITERATURE REVIEW

This section critically examines the existing body of knowledge surrounding key constructs that shape Supply Chain 5.0 (SC5.0) preparedness, particularly within the context of public sector enterprises. It focuses on five foundational pillars: (a) Technological Readiness, encompassing enablers such as IoT, AI, ERP, and Blockchain; (b) Leadership and Change Management, highlighting the strategic role of top management in transformation efforts; (c) Human-AI Collaboration Capability, emphasizing synergy between digital systems and human decision-making; (d) Workforce Skills and AI Literacy, addressing the digital competencies required to operate in SC5.0 environments; and (e) Organizational Learning and Innovation, which underscore the need for a culture of continuous improvement. These variables together provide a comprehensive framework for evaluating digital and organizational readiness in the evolving supply chain environment. As summarized in Table 2, prior studies have examined discrete dimensions of SC5.0 such as IoT-driven resilience (Al-Talib *et al.*, 2020), AI-enabled transparency (Modgil *et al.*, 2022), innovation leadership (Bag *et al.*, 2021), and human–AI alignment (Sauer & Burggräf, 2025), often within narrow sectoral or conceptual contexts. While these works provide valuable insights, they remain fragmented, context-specific, or limited to single-method approaches. In contrast, the present study differs by integrating these dimensions into a holistic, empirically validated framework that combines SEM for causal testing, TOPSIS for benchmarking, and ANN for predictive validation.

Applied to large-scale survey data from Indian capital-intensive PSUs, this hybrid approach not only identifies leadership and agility as dominant readiness drivers but also generates a comparative SC5.0 Readiness Index, offering both theoretical novelty and practical benchmarking value.

Table 2 - Comparative Summary of Literature on Key Dimensions of Supply Chain 5.0

Theme	Author(s) & Year	Context/Setting	Methodology	Key Findings	Contribution	Limitations
Technological Readiness	Al-Talib *et al.* (2020)	Manufacturing SCM	Conceptual + Case Study	IoT enhances SC resilience via real-time monitoring and alerts	Enables predictive SC systems	Context-specific; lacks cross-sector validation
	Modgil *et al.* (2022)	Global supply chains	Expert Interviews (n=35)	AI supports transparency, procurement, last-mile optimization	Positions AI as dynamic SC capability	Limited to COVID-related disruptions
Leadership & Change Management	Bag *et al.* (2021)	Healthcare SC	Mixed-method (PLS-SEM + interviews)	Innovation leadership enhances responsiveness via BDA	Empirical link between leadership and SC innovation	Context-specific to healthcare
	Dalporto & Venn (2020)	Dormakaba UK	Case Study	Control tower boosts transparency, performance visibility	Real-time decision-making across SC tiers	Single firm; lacks generalizability
	Frankowska & Rzeczycki (2020)	EU	Case Study	Distributed digital leadership in SCs	Networked leadership model	Limited data scope
Human–AI Collaboration	Dwivedi (2019)	Chinese digital firms	Panel Data (4900 obs)	Human-AI balance improves SC efficiency & digitalization	Contextualizes AI gains in digital maturity	Limited to digital media
	Sauer & Burggräf (2025)	Manufacturing	Framework Development	Decision-mapping improves AI-human alignment	Proposes hybrid intelligence model	Needs empirical validation
	Riad *et al.* (2024)	Global SC	Conceptual	AI enhances real-time response & disruption recovery	AI as resilience enabler	Theoretical

Theme	Author(s) & Year	Context/Setting	Methodology	Key Findings	Contribution	Limitations
Workforce Skills & AI Literacy	Foroughi (2021)	Malaysia	Job Ad Content Analysis	10 skills incl. analytics, PM, forecasting vital	Reflects post-COVID talent needs	Country-specific
	Modgil *et al.* (2022)	Global	Bibliometric (n=270)	Four AI literacy dimensions defined	Holistic view of AI literacy	Fragmented literature; lacks theory
	Queiroz *et al.* (2021)	Industry 4.0	Narrative Review	Digital skills must evolve with tech	DSCC framework for capability alignment	Early-stage framework
Organizational Learning & Innovation	Eryarsoy *et al.* (2022)	Indonesian Universities	SEM using SmartPLS	Learning improves hard/soft skills and performance	OL as performance catalyst	Focus on education sector
	Gupta *et al.* (2020)	Indian Manufacturing	BWM	Lack of R&D & innovation top barriers	Strategic prioritization of barriers	Strategy generalization needed
	Malik *et al.* (2021)	Australian Firms	TOE Framework + Interviews	Learning & top management drive blockchain adoption	Links OL to digital tech uptake	Australia-specific context
Process Integration & Policy Compliance	Benzidia *et al.* (2021)	French Hospitals	PLS-SEM	BDA-AI improves green SC collaboration	OIPT applied to healthcare SC	Limited to hospitals
	Wong *et al.* (2022)	SMEs	Survey + PLS-SEM	Policy awareness drives cybersecurity compliance	PMT framework for SC reactivity	Vulnerability not significant

3 METHODOLOGY

3.1 Research Design

This study adopts a quantitative, multi-method research design to assess the preparedness of Indian Public Sector Units (PSUs) for Supply Chain 5.0 (SC5.0) as shown in Figure 1. The design integrates Structural Equation Modeling (SEM) for causal path analysis, Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) for multi-criteria ranking, and Artificial Neural Networks (ANN) for predictive learning. This mixed method equips a inclusive assessment of the latent constructs in persuading SC5.0 readiness and simplifies cross-validation of revelations through triangulation.

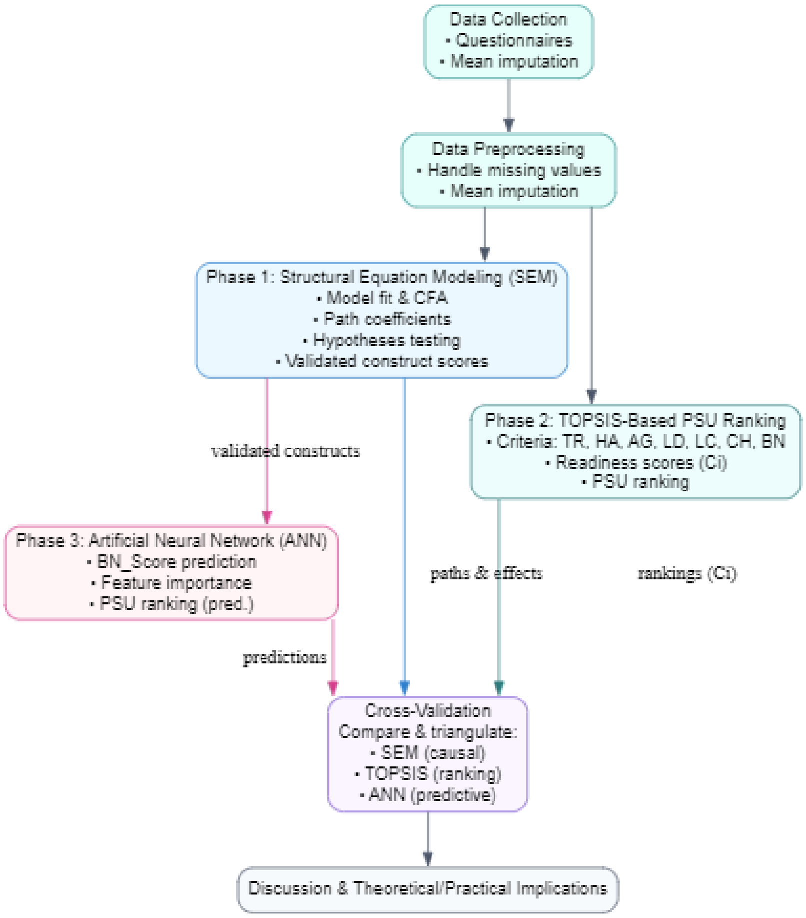

Figure 1 - Workflow of Methodological Approach for PSU Readiness Modelling

As illustrated in Figure 1, the study follows a three-phase methodological framework with cross-validation. Phase 1 (SEM) is employed to test hypothesized causal relationships among latent constructs and identify significant drivers of SC5.0 readiness. Phase 2 (TOPSIS) independently applies multi-criteria decision-making to the construct-level scores to generate a comparative SC5.0 Readiness Index and rank PSUs. These two phases are not directly compared in isolation but are designed to provide complementary perspectives—SEM for causal validation and TOPSIS for benchmarking.

The findings from Phase 1 (SEM), particularly the construct scores and validated causal paths, inform the input structure for Phase 3 (ANN), which uses predictive modeling to test robustness and identify variable importance. In parallel, the outputs from Phase 2 (TOPSIS) are incorporated into the Cross-Validation stage, where PSU rankings and readiness drivers derived from SEM, TOPSIS, and ANN are compared for convergence. This triangulated design ensures that causal, prescriptive, and predictive insights are integrated for both theoretical and practical contributions.

3.2 Sampling and Data Collection

To look into further the vigilance of capital-intensive Indian Public Sector Units (PSUs) for shifting towards Supply Chain 5.0 (SC5.0), primary data was accumulated through a structured questionnaire administered to pertinent professionals over six major PSUs. The sampling tactics embraced was purposive, targeting individuals in roles directly connected with supply chain operations, strategic planning, IT systems, and tech- driven change. This technique assured that the perceptions gathered were rooted in proficiency and organizational relevance, thereby improving the validity of the findings. Steel Authority of India Limited (SAIL), Gas Authority of India Limited (GAIL), Hindustan Aeronautics Limited (HAL), National Thermal Power Corporation (NTPC), Bharat Electronics Limited (BEL), and Bharat Heavy Electricals Limited (BHEL) are the six representative PSUs from various but capital-intensive industries that were the focus of the study. In order to ensure comparability in terms of organizational structure, technical infrastructure, and tech revolution capability, these organizations were selected to represent diversity in industrial domains.

Respondents had to meet inclusion requirements that verified they had at least three years of relevant work experience in their company, as well as direct involvement in IT projects. The primary data collection was carried out over a period of three months (March–May 2024). Structured questionnaires were distributed through professional networks and PSU mailing lists, with multiple reminders sent to maximize response rates. This timeline allowed sufficient coverage across the six targeted PSUs while ensuring data recency and reliability. Through professional networks and organizational mailing lists, 540 survey invitations were distributed in total. Following several alerts and concerted efforts, 485 fully completed and significant insights were obtained, resulting in an 89.81% success rate. The usual structural equation modeling (SEM) requirements, which call for at least 10 responses per item, are met by this substantial sample size. The instrument has 35 observed variables (items), hence a minimum sample size of 350 was needed. For both SEM and Artificial Neural Network (ANN) analyses, the final sample size of 485 thus surpasses methodological requirements, allowing for dependable model calibration and generalizability. Supply chain managers (34%), operations and plant supervisors (27%), IT and digital transformation officers (22%), and senior executive leadership (17%) comprised the respondents' diverse range of job domains. A thorough understanding of SC5.0 readiness from both a strategic and operational standpoint was ensured by this cross-functional representation. Richer insights into the factors that facilitate and hinder technology-driven transformation in hierarchical PSU structures were also made possible by the range of responder roles. Technological Readiness (TR), Human-AI Collaboration (HA), Agility (AG), Leadership Dynamics (LD), Learning Culture (LC), Change Handling (CH), and Business Network Integration (BN) were the seven latent constructs that composed the survey instrument. Each problem was scored on a five-point Likert scale, where 1 represented "Strongly Disagree" and 5 represented "Strongly Agree." 15 experts comprising academic researchers and PSU executives conducted the pilot test of the questionnaire to validate its relevance, clarity, as well as content validity. Based on their feedback, minor revision was undertaken before full-scale roll-out. Through secure access URLs and in-house PSU communication channels, the data collection process was conducted in a three-month span using Google Forms. Table 3 illustrates Distribution of survey respondents across various Public Sector Units (PSUs) categorized by professional roles, including SCM managers, operations heads, IT professionals, and senior leadership.

Table 3 - Distribution of Respondents by PSU and Professional Role

PSU	SCM Managers	Operations Heads	IT Professionals	Senior Leader ship	Total
SAIL	30	22	18	15	85
GAIL	28	20	17	10	75
HAL	24	18	16	12	70
NTPC	26	21	15	13	75
BHEL	32	25	14	14	85
BEL	25	23	16	11	75
Total	165	129	96	75	485

3.3 Instrument Development

The survey instrument was designed using validated scales from prior studies, carefully adapted to the Supply Chain 5.0 (SC5.0) context of Indian Public Sector Units (PSUs). Each construct was measured on a five-point Likert scale, where 1 represented Strongly Disagree and 5 represented Strongly Agree. The constructs, number of items, and representative sample statements are shown in Table 4.

To ensure content validity and methodological transparency, the items were adapted from widely recognized and previously validated sources. Specifically:

- Technological Readiness (TR): adapted from established technology readiness and digital adoption scales (Parasuraman, 2000; Zhang *et al.*, 2023).
- Human–AI Collaboration (HA): drawn from prior frameworks on AI adoption and human–machine collaboration (Dwivedi *et al.*, 2019; Sauer & Burggräf, 2024; Yaroson *et al.*, 2025).
- Organizational Agility (AG): adapted from supply chain agility and resilience measures (Trabucco & De Giovanni, 2021).
- Leadership Dynamics (LD): adapted from innovation leadership and change management scales in supply chain and organizational studies (Bag *et al.*, 2021; Dalporto & Venn, 2020).
- Learning Culture (LC): derived from organizational learning and continuous improvement scales (Eryarsoy *et al.*, 2022).
- Change Handling (CH): adapted from change management and readiness-for-change scales (Demir *et al.*, 2022).
- Business Network Integration (BN): based on measures of inter-organizational collaboration and digital supply chain integration (Frankowska & Rzeczycki, 2020; Benzidia *et al.*, 2021).

This systematic adoption of validated scales ensures that the constructs reflect established theoretical and empirical foundations while being tailored to the SC5.0 environment of Indian PSUs. The pilot testing process (n = 15 experts, including academic researchers and PSU executives) further confirmed clarity, contextual relevance, and reliability, after which minor refinements were made prior to full-scale deployment.

Table 4 - Latent Constructs and Sample Items

Construct	Code	Item Statement
Technological Readiness (TR)	TR1	Our systems are digitally integrated and interoperable.
	TR2	We use advanced digital technologies such as IoT and AI in operations.
	TR3	Our IT infrastructure supports end-to-end supply chain visibility.
	TR4	We have adopted ERP systems for real-time process integration.
	TR5	Data-driven tools are widely used for decision-making.
Human–AI Collaboration (HA)	HA1	AI tools are embedded in daily operations.
	HA2	Employees collaborate with AI systems in decision-making.
	HA3	AI enhances our ability to predict and respond to disruptions.
	HA4	There is trust in AI-generated recommendations.
Agility (AG)	AG1	Our unit can quickly respond to supply disruptions.
	AG2	Processes are flexible to adapt to sudden changes.
	AG3	We can scale operations up or down effectively.
	AG4	Our supply chain decisions are taken with minimal delays.

Leadership Dynamics (LD)	LD1	Leadership actively drives digital transformation.
	LD2	Top management allocates sufficient resources for innovation.
	LD3	Leaders communicate a clear vision for SC5.0.
	LD4	Leadership supports cross-functional collaboration.
Learning Culture (LC)	LC1	We invest regularly in skill upgradation and learning.
	LC2	Employees are encouraged to experiment with new digital tools.
	LC3	There is a culture of continuous improvement.
	LC4	Knowledge sharing across teams is actively promoted.
Change Handling (CH)	CH1	We have structured processes to manage change.
	CH2	Employees are supported during periods of transition.
	CH3	Resistance to digital initiatives is effectively managed.
	CH4	Change initiatives are implemented smoothly.
Business Network Integration (BN)	BN1	We maintain strong data-driven links with suppliers and partners.
	BN2	Information is shared seamlessly across the supply chain network.
	BN3	Our collaborations with external partners are digitally enabled.
	BN4	We engage in joint problem-solving with supply chain partners.

A. Variables and Construct Operationalization

In this study, seven latent constructs indicative of the key aspects of Supply Chain 5.0 (SC5.0) readiness in Indian Public Sector Units (PSUs) were measured. A 5-point Likert scale where 1 represents strongly disagree and 5 represents strongly agree was used to measure each concept. The composite score was calculated by using the mean of each construct's valid item responses. Table 5 describes definitions of latent constructs along with their conceptual descriptions and corresponding measurement indicators used for evaluating SC5.0 readiness.

Table 5 - Construct Descriptions and Indicators

Code	Construct	Conceptual Definition	Measurement Items
TR	Technological Readiness	The degree to which the PSU has implemented digital infrastructure, IoT, automation, and smart technologies.	TR1–TR5
HA	Human-AI Collaboration	The extent to which employees collaborate with AI systems, including co-decision-making, training, and AI augmentation.	HA1–HA4
AG	Organizational Agility	The capacity of the PSU to respond to rapid changes through flexible	AG1–AG4

		decision-making, adaptive processes, and speed of execution.	
LD	Leadership Dynamics	The strategic role of top management in championing digital transformation, allocating resources, and enabling a forward-looking vision.	LD1–LD4
LC	Learning Culture	The presence of continuous learning, training opportunities, innovation culture, and openness to new technologies.	LC1–LC4
CH	Change Handling	The organization's ability to manage resistance, change fatigue, and smooth transition during digital interventions.	CH1–CH4
BN	Business Network Integration	The extent of collaboration with external partners including suppliers, customers, and digital ecosystems. Considered the outcome/dependent variable in SEM and ANN.	BN1–BN4

B. Latent vs Observed Variables

Each construct was derived from a number of observed indicators (items) and is a proxy for a latent variable. They were built upon validated scales in organizational behavior literature, Industry 5.0, and supply chain digitalization.

Scale Reliability and Aggregation

Each construct was tested for internal consistency using Cronbach's alpha. Composite construct scores were computed as:

$$Construct\ Score_1 = \frac{1}{n}\sum_{j=1}^{n} X_{ij} \tag{1}$$

Where:

- i is the respondent
- j is the item index under a specific construct
- Xij is the Likert score for item j of respondent i.

Only records with complete values across a construct's items were retained for averaging to ensure data reliability and validity.

3.4 Analytical Framework

This study adopts a three-phase analytical framework combining Structural Equation Modeling (SEM), Multi-Criteria Decision Making (TOPSIS), and Artificial Neural Networks (ANN) to comprehensively assess Supply Chain 5.0 (SC5.0) readiness across Indian Public Sector Units (PSUs). Each phase is methodologically and mathematically distinct, providing robust insights from confirmatory, prescriptive, and predictive perspectives.

Phase 1: Structural Equation Modeling (SEM)

Structural Equation Modeling (SEM) was employed to test the hypothesized causal relationships among latent constructs derived from the conceptual framework. SEM integrates both the measurement model and the structural model:

Measurement model (CFA):

$$x = \Lambda_x \xi + \delta \tag{2}$$

where:
x is the vector of observed indicators,
Λ_x is the factor loading matrix,
ξ is the latent construct vector,
δ is the measurement error vector.

Structural model:

$$\eta = B_\eta + \Gamma\xi + \zeta \tag{3}$$

where:
η = endogenous latent variables,
ξ = exogenous latent variables,
B = relationships among endogenous variables,
Γ = effects of exogenous on endogenous variables,
ζ = structural error terms.

Model estimation was performed using the **maximum likelihood (ML)** method via Python's semopy package. Hypothesis testing was conducted at a significance level of $p<0.05$, and model fit was evaluated using standard indices such as Comparative Fit Index (CFI), Tucker–Lewis Index (TLI), and Root Mean Square Error of Approximation (RMSEA).

Phase 2: Multi-Criteria Decision Making (TOPSIS)

To comparatively assess the SC5.0 readiness of PSUs, the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) was applied to the seven latent construct scores: TR, HA, AG, LD, LC, CH, and BN.

The TOPSIS procedure involves the following key steps:

1. Normalization of the Decision Matrix:

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}} \tag{4}$$

2. Weighted Normalized Decision Matrix:

$$v_{ij} = w_j \cdot r_{ij} \tag{5}$$

where wj represents the weight for criterion j, assumed equal for all constructs in this study.

3. Determination of Ideal and Negative-Ideal Solutions:

$$A^+ = \{\max(v_{ij})\}, A^- = \{\min(v_{ij})\} \tag{6}$$

4. Separation Measures

$$S_i^+ = \sqrt{\sum_{j=1}^{n}(v_{ij} - A_j^+)^2}, \quad S_i^- = \sqrt{\sum_{j=1}^{n}(v_{ij} - A_j^-)^2} \tag{7}$$

5. Relative Closeness to the Ideal Solution:

$$C_i = \frac{S_i^-}{S_i^+ + S_i^-} \tag{8}$$

The final output yields a composite TOPSIS score Ci for each PSU, enabling rank-ordering of units based on their proximity to the ideal readiness profile.

Phase 3: Predictive Modeling Using Artificial Neural Networks (ANN)

The ANN model followed a feed-forward fully connected architecture implemented using TensorFlow/Keras. The input layer consisted of 6 nodes, each representing one of the independent construct scores (TR_Score, HA_Score, AG_Score, LD_Score, LC_Score, CH_Score) as shown i After splitting the data 80-20 into training and test groups, the input variables were scaled with the Standard Scaler. This paper had a 10% validation split for convergence monitoring during training. The performance of the ANN was assessed with significant regression metrics such as R^2 (coefficient of determination), RMSE (root mean square error), and MAE (mean absolute error), which validated its outstanding predictive validity. This phase proved the efficacy of machine learning in facilitating strategic readiness assessments and re-affirmed leadership dynamics as the most significant predictor. The evaluation approach represented in the table shows a three-step strategy intended to answer the main research questions regarding SC5.0 preparedness within Indian PSUs. Table 6 Research Questions Addressed by the Framework

Phase 1 answers RQ2 and RQ4 directly through the application of Structural Equation Modeling (SEM) to explore the causal structures between main organizational dimensions for hypothesis validation and the identification of determinants influencing SC5.0 readiness. Phase 2 utilizes a multi-criteria decision-making approach named TOPSIS to assess and rank PSU readiness scores from normalized construct data. This adequately responds to comparative level RQs 1 and 3. Finally, Phase 3 considers a predictive Artificial Neural Network (ANN) model that utilize input variables like agility and leadership to measure SC5.0 readiness. This complements SEM findings and offers additional information on key elements, which strengthens RQ2 and RQ4. Taken together, these combined methodologies provide a strong, triangulated method for both practical assessment and theoretical rationale in Figure 2. This was followed by two hidden layers: the first with 16 neurons and the second with 8 neurons, both using Rectified Linear Unit (ReLU) activation functions to capture nonlinear relationships. The output layer included a single neuron with linear activation, suitable for continuous target prediction. The model was trained using the Adam optimizer and mean squared error (MSE) as the loss function. Table 6 Overview of the three-phase analytical framework detailing the methods used.

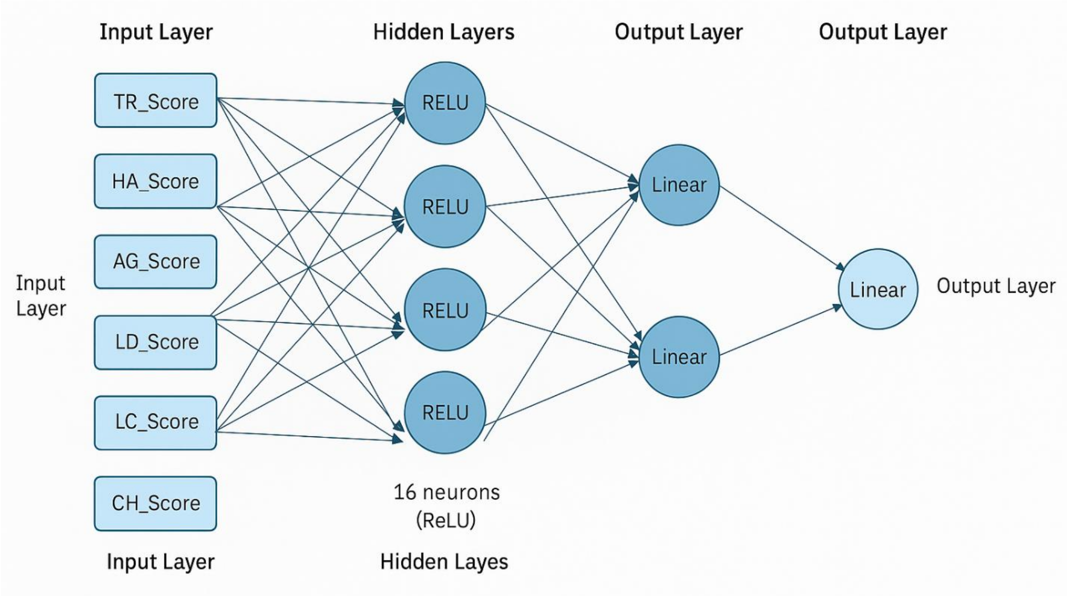

Figure 2 - Predictive Modelling using Artificial Neural Networks

Table 6 - Research Questions Addressed by the Framework

Phase	Method	Purpose	Linked Research Question
Phase 1	SEM	Hypothesis testing and structural validation	RQ2, RQ4
Phase 2	TOPSIS	PSU ranking on SC5.0 readiness	RQ1, RQ3
Phase 3	ANN	Prediction and variable influence	RQ2, RQ4

3.5 Data Preprocessing and Handling Missing Values

For the Artificial Neural Network (ANN) modeling stage, the criterion was keener. Full cases, or rows with no missing values in any of the construct-level scores (such as TR_Score, HA_Score, or LD_Score), were the only ones used for coaching and measurement. By opting to instruct the prediction framework using high-integrity data, problems arising from imputed inputs that can impact the learning process were shunned.

All continuous numerical variables incorporated in the ANN (i.e., the six input construct scores) were standardized using Z-score normalization to enhance model performance and training effectiveness. To do this, the Standard Scaler function from the sklearn. preprocessing package was utilized. The following method was used to mathematically alter each variable x:

$$x' = \frac{x-\mu}{\sigma} \tag{9}$$

where σ is the variable's standard deviation and μ is its mean. Faster convergence and improved generalization during ANN training were made possible by this adjustment, which made sure that all input features were on the same scale (mean = 0, standard deviation = 1).

4 RESULTS AND FINDINGS

4.1 Descriptive Statistics and Initial Observations

A. Overview of Descriptive Metrics

In this section the initial descriptive analysis and the SC5.0 preparedness dataset, which concludes 485 valid responses from professionals in seven capital-intensive Indian Public Sector Units (PSUs) are provided. Both item-level responses and computed construct-level scores are incorporated in the dataset for seven latent constructs: Technological Readiness (TR), Human-AI Collaboration (HA), Agility (AG), Leadership Dynamics (LD), Learning Culture (LC), Change Handling (CH), and Business Network Integration (BN). Table 7 gives a summary of the descriptive findings, which highlight importantt distributional features for each construct and item. Measures such as the mean, standard deviation, quartile ranges and lowest and highest values give information on how similar or dissimilar respondents are from each other.

Table 7 - Descriptive Statistics of Survey Items and Construct Scores (n = 485)

Construct	Items	Mean	Std Dev	Min	25%	Median	75%	Max
TR	TR1–TR5	3.035 – 3.115	0.946 – 0.966	1.00	2.00	3.00	4.00	5.00
HA	HA1–HA4	2.774 – 2.835	1.072 – 1.146	1.00	2.00	3.00	4.00	5.00
AG	AG1–AG4	2.967 – 3.029	0.849 – 0.965	1.00	2.00	3.00	4.00	5.00
LD	LD1–LD4	3.312	0.738	1.50	2.67	3.33	4.00	5.00
LC	LC1–LC4	2.472	0.599	1.00	2.00	2.50	3.00	4.50
CH	CH1–CH4	2.427	1.027	1.00	1.50	2.25	3.00	5.00
BN	BN1–BN4	2.966	0.690	1.00	2.50	2.75	3.50	4.67

Note: Construct scores were computed as average of respective item scores. Items with missing values were excluded pairwise.

Significant trends in PSU preparedness characteristics are revealed by the initial examination of composite scores. With a moderate average (~3.04), Technological Readiness (TR) showed a continuous shift toward digital transformation. Human-AI Collaboration (HA), on the other hand, had the lowest mean (~2.80) and the most variation, indicating that AI adoption was not uniform among units. Responses to agility (AG) were comparatively balanced, indicating consistent but changing adaptation. The strategic importance of top leadership was highlighted by Leadership Dynamics (LD), which had the highest mean (3.31). The lower scores for Learning Culture (LC) and

Change Handling (CH) (both <2.50), however, suggest possible deficiencies in soft skills necessary for Supply Chain 5.0. Lastly, the moderate mean (~2.97) and large dispersion of Business Network Integration (BN) showed that external cooperation strategies vary.

B. Reliability and Validity Assessment.

To evaluate measurement reliability, Cronbach's alpha, Composite Reliability (CR), and Average Variance Extracted (AVE) were computed for each construct (Table 8). Results indicate that most constructs exceeded the recommended reliability thresholds (Cronbach's α > 0.70; CR > 0.70; AVE > 0.50), confirming internal consistency and convergent validity (Hair *et al.*, 2019; Hu & Bentler, 1999; Byrne, 2010). Specifically, Human–AI Collaboration (α = 0.838; CR = 0.987; AVE = 0.948), Agility (α = 0.892; CR = 0.987; AVE = 0.951), and Leadership Dynamics (α = 0.725; CR = 0.983; AVE = 0.937) demonstrated strong reliability. Technological Readiness also met the acceptable threshold (α = 0.710; CR = 0.976; AVE = 0.891). However, Learning Culture recorded a lower Cronbach's α (0.453), indicating weaker internal consistency, though its CR (0.961) and AVE (0.859) suggest that convergent validity was still achieved. Overall, these results establish that the measurement model is sufficiently reliable and valid for subsequent SEM analysis.

Table 8 - Reliability and Validity of Constructs

Construct	Cronbach's α	Composite Reliability (CR)	Average Variance Extracted (AVE)
Technological Readiness (TR)	0.710	0.976	0.891
Human–AI Collaboration (HA)	0.838	0.987	0.948
Agility (AG)	0.892	0.987	0.951
Leadership Dynamics (LD)	0.725	0.983	0.937
Learning Culture (LC)	0.453	0.961	0.859

4.2 Structural Equation Modeling (SEM) Results

To authenticate the hypothesized relationships between the constructs underpinning Supply Chain 5.0 preparedness in Indian PSUs, a structural equation modeling (SEM) technique was adoted using the maximum likelihood estimation method. As shown in Table 9, the model achieved satisfactory fit across multiple indices (CFI = 0.9297, TLI = 0.9218, RMSEA = 0.0467, GFI = 0.8725, AGFI = 0.8582, χ^2/df = 2.05). These values all fall within the recommended ranges (Hu & Bentler, 1999; Byrne, 2010; Kline, 2016), confirming that the measurement and structural models are well-specified.

Table 9 - SEM Model Fit Indices

Fit Index	Value	Threshold	Interpretation	References
CFI	0.9297	> 0.90	Acceptable Fit	Hu & Bentler (1999); Hair *et al.* (2019)
TLI	0.9218	> 0.90	Acceptable Fit	Hu & Bentler (1999)
RMSEA	0.0467	< 0.05	Close Fit	Steiger (1990); Hu & Bentler (1999)
GFI	0.8725	> 0.85	Good Fit	Byrne (2010)
AGFI	0.8582	> 0.85	Good Fit	Byrne (2010)
χ^2/df	2.05	< 3	Acceptable	Hair *et al.* (2019); Kline (2016)
AIC	136.91	-	Lower is Better	
LogLik	1.5463	-	Maximized	

***C.* Path Coefficients and Hypothesis Testing**

The standardized path estimates revealed both expected and unexpected relationships among the constructs. Table 6.3 presents a summary of significant paths with their respective regression weights (β), standard errors, z-values, and p-values. The structural model depicted in Figure 3 visually represents the hypothesized relationships among the latent variables driving Supply Chain 5.0 readiness in Indian public sector undertakings (PSUs). This model incorporates both measurement and structural components, indicating the strength and directionality of each relationship through path coefficients (standardized estimates) and significance levels (p-values). Circles denote latent constructs (e.g., TR, HA, AG, LD), while rectangles represent observed indicator variables.

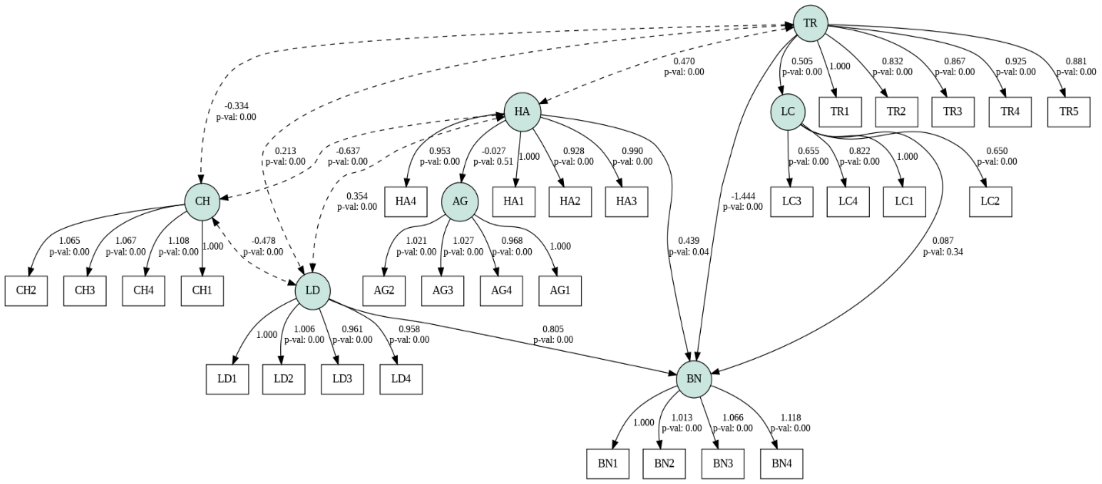

Figure 3 - SEM Path Diagram Depicting the Interrelationships Among TR, HA, AG, LD, LC, CH, and BN Constructs

The solid lines represent statistically significant paths ($p < 0.05$), whereas dashed lines denote non-significant relationships. As illustrated, the most pronounced positive relationship is between Leadership Dynamics (LD) and Business Network Integration (BN) ($\beta = 0.805$, $p < 0.001$), supporting H2, and confirming that strong leadership contributes directly to external readiness and strategic partnerships. This aligns with prior studies such as Rai *et al.* (2021), who highlighted the catalytic role of visionary leadership in digital supply ecosystems. Similarly, Human-AI Collaboration (HA) positively influences BN ($\beta = 0.439$, $p = 0.038$), validating H3 and indicating that AI-augmented processes enhance stakeholder coordination and information flow. Interestingly, Technological Readiness (TR) exhibits a negative association with BN ($\beta = -1.444$, $p < 0.001$), contradicting the assumption of its direct positive influence (H1). This implies that technology implementation, in the absence of complementary soft enablers like culture and leadership, may lead to siloed systems or inefficiencies. The path from Learning Culture (LC) to BN ($\beta = 0.087$, $p = 0.337$) and from HA to Agility (AG) ($\beta = -0.027$, $p = 0.510$) were found statistically insignificant, suggesting limited standalone influence. This underlines the importance of integrated strategies over isolated soft or technological interventions. Table 10 presents critical standardized path estimates and associated significance levels. The bolded coefficients highlight the paths that are both statistically and practically significant. For instance, the strong positive effect of LD on BN not only confirms theoretical expectations but also emphasizes the real-world implication that leadership remains the most actionable lever in enhancing readiness across PSUs. SEM results offer empirically validated insights into the hierarchical influence of constructs, where leadership, AI collaboration, and inter-organizational synergies collectively shape the trajectory toward Industry 5.0 transformation.

Table 10 - Significant SEM Path Coefficients

Predictor → Outcome	Estimate (β)	Std. Error	z-value	p-value	Interpretation
LD → BN (H2)	0.805	0.131	6.157	< 0.001	Strongest positive influence
HA → BN (H3)	0.439	0.212	2.074	0.038	Moderate positive influence

TR → BN (H1)	−1.444	0.309	−4.673	< 0.001	Significant negative association
LC → BN (H4)	0.087	0.090	0.961	0.337	Not significant
HA → AG (H5)	−0.027	0.042	−0.659	0.510	Not significant

4.3 PSU-Level Readiness Assessment using TOPSIS

To derive a quantitative readiness index across Public Sector Units (PSUs), the TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) method was employed using normalized composite scores of seven latent constructs in Table 11 Technological Readiness (TR), Human-AI Collaboration (HA), Agility (AG), Leadership Dynamics (LD), Learning Culture (LC), Change Handling (CH), and Business Network Integration (BN). These factors encompass the organizational and technological readiness essential for the implementation of Supply Chain 5.0 (SC5.0). The rankings were then derived by sorting these coefficients in descending order.

Table 11 - PSU-Level Construct Scores and TOPSIS Ranking

Rank	PSU Name	TR Score	HA Score	AG Score	LD Score	LC Score	CH Score	BN Score	TOPSIS Score
1	SAIL	3.0351	2.7641	2.9950	3.4388	2.4157	2.2882	3.0673	0.5223
2	GAIL	3.1861	2.9067	2.9762	3.3016	2.4970	2.4196	2.8552	0.4991
3	HAL	3.0047	2.7774	3.0772	3.2713	2.5142	2.4665	2.9573	0.4650
4	NTPC	3.0617	2.7728	3.0486	3.2639	2.5010	2.4117	2.9435	0.4525
5	BHEL	2.9902	2.8179	2.9976	3.2845	2.5143	2.4690	3.0071	0.4331
6	BEL	2.9313	2.7703	3.0325	3.3079	2.3953	2.5142	2.9736	0.2733

From the rankings, SAIL emerges as the most SC5.0-ready PSU, attaining the highest TOPSIS score of 0.5223, which reflects its particularly strong performance in Leadership Dynamics (3.4388) and Business Network Integration (3.0673). These results suggest that SAIL is organizationally aligned with SC5.0 transformation priorities such as strategic foresight and stakeholder collaboration. GAIL follows closely with a high score in Technological Readiness (3.1861) and Human-AI Collaboration (2.9067), indicating solid digital infrastructure and early AI integration. Meanwhile, HAL and NTPC also show competitive readiness, especially in agility and leadership dimensions. Conversely, BEL ranks lowest, with the lowest TOPSIS score (0.2733) among the selected units, mainly due to comparatively lower scores in Learning Culture and HA, indicating potential resistance to change and underdeveloped AI collaboration frameworks.

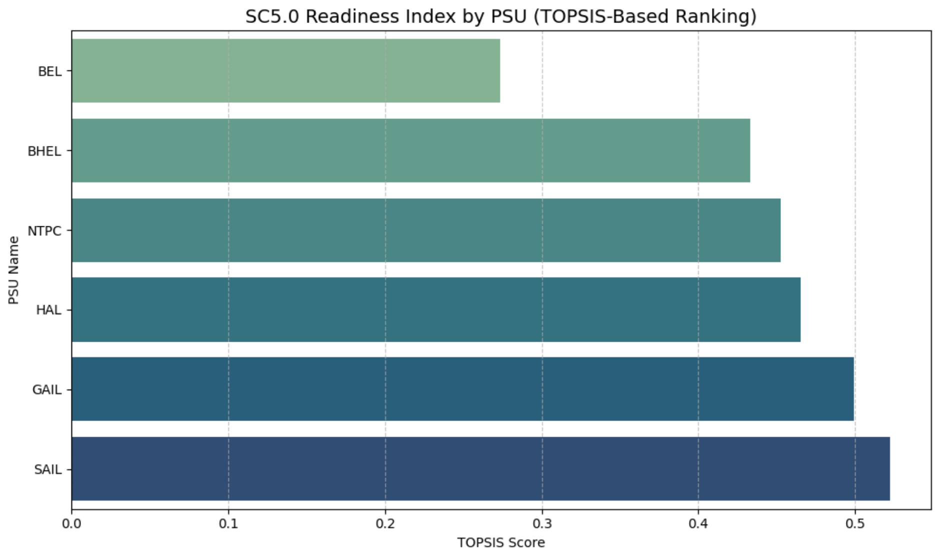

Figure 4 - PSU Readiness Rankings based on TOPSIS

Figure 4 illustrates a horizontal bar chart that ranks six prominent Public Sector Units (PSUs) based on their composite Supply Chain 5.0 (SC5.0) readiness scores, derived using the TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) method. The X-axis indicates the normalized readiness scores (ranging from 0 to 1), while the Y-axis displays the PSU names in descending order of readiness. Notably, SAIL secures the top position with a score of 0.5223, owing to its robust leadership dynamics and strong trust-building capacity (as evidenced by LD and BN scores). It is followed by GAIL with a score of 0.4991, highlighting its technological maturity and relatively consistent integration of human-AI collaboration. HAL and NTPC emerge as mid-performing organizations (scores around 0.45), reflecting moderate proficiency in agility and learning adaptability, although they slightly lag in strategic leadership. BHEL, with a score of 0.4331, demonstrates a stable yet unremarkable performance across core readiness dimensions. At the lower end, BEL registers the weakest readiness score of 0.2733, indicating notable deficiencies in soft transformation levers such as adaptability, learning culture, and digital collaboration. Overall, this figure clearly captures the variation in Industry 5.0 preparedness across PSUs, signaling that while some entities like SAIL and GAIL are strategically aligned with SC5.0 principles—namely resilience, innovation readiness, and digital integration—others may require tailored policy support, leadership reform, and workforce retraining to bridge the readiness gap and participate effectively in the evolving industrial ecosystem.

4.4 Predictive Modelling using Artificial Neural Networks (ANN)

To provide predictive validation, a feed-forward fully connected Artificial Neural Network was implemented using TensorFlow/Keras. The model architecture consisted of an input layer with six nodes (representing TR, HA, AG, LD, LC, and CH construct scores), two hidden layers with 16 and 8 neurons respectively, both using Rectified Linear Unit (ReLU) activation, and a single output neuron with linear activation for continuous prediction of BN_Score. Data were split into 80% training and 20% testing sets, with a 10% validation split applied during training. Input features were standardized using Z-score normalization via the StandardScaler function. The model was trained using the Adam optimizer with Mean Squared Error (MSE) as the loss function. Model performance was evaluated using R^2, RMSE, and MAE, ensuring both accuracy and generalization. The ANN model demonstrated strong predictive capability, achieving an R^2 value of 0.8841, indicating that approximately 88.4% of the variance in Business Network Integration (BN_Score) could be explained by the input variables. The model also exhibited low Root Mean Squared Error (RMSE = 0.0211) and Mean Squared Error (MSE = 0.0004), reinforcing its robustness and generalization potential across test samples.

Feature Importance Analysis

Permutation-based feature importance was applied to interpret the ANN model's decision-making behavior. As depicted in Table 12 Leadership Dynamics (LD_Score) emerged as the most influential predictor (weight = 0.6434 ± 0.1674), followed by Agility (AG_Score) and Change Handling (CH_Score). Learning Culture (LC) and Technological Readiness (TR) also contributed meaningfully, while Human-AI Collaboration (HA_Score) showed relatively lower influence.

Table 12 - ANN Feature Importance Scores

Rank	Feature	Weight ± Std. Deviation
1	LD_Score	0.6434 ± 0.1674
2	AG_Score	0.2440 ± 0.0599
3	CH_Score	0.2152 ± 0.0493
4	LC_Score	0.1877 ± 0.0456
5	TR_Score	0.1660 ± 0.0545
6	HA_Score	0.1338 ± 0.0498

This finding aligns with the SEM path diagram, where Leadership → BN had the strongest path coefficient (β = 0.805), and with the TOPSIS rankings, where SAIL and GAIL performed best due to high leadership and agility scores. The ANN model thus offers triangulated validation that leadership is a critical enabler of SC5.0 preparedness in public sector enterprises.

ANN-Based PSU Ranking

The ANN model supports that change-handling, agility, and leadership are drivers of Industry 5.0 readiness supported by SEM and TOPSIS outcomes. PSU rankings affirm predictive consistency with SAIL, GAIL, and HAL ranking first in all methods as shown in Table 13.

Table 13 - PSU-Level SC5.0 Readiness Rankings using ANN Predictions

Rank	PSU Name	Mean ANN-Predicted BN Score
1	SAIL	3.08
2	GAIL	2.99
3	HAL	2.95
4	NTPC	2.92
5	BHEL	2.90
6	BEL	2.78

4.5 Cross-Method Comparison and Consistency

In order to ascertain methodological strength, a comparative SEM, TOPSIS, and ANN analysis pointed towards high convergence, where all three methods uniformly highlighted leadership dynamics and organizational agility as leading drivers of SC5.0 readiness across Indian PSUs.

- SEM findings highlighted that leadership dynamics (LD) had the strongest positive path to business network integration (BN) (β = 0.805, $p < 0.001$), signifying the strategic role of leadership in orchestrating readiness.
- TOPSIS rankings placed SAIL and GAIL at the top, both of which had notably high LD and TR scores as shown in table 14, reinforcing the latent influence of leadership and trust dimensions.
- ANN modeling further confirmed the dominance of LD_Score (weight = 0.6434 ± 0.1674), followed by AG_Score and CH_Score, validating the importance of leadership, agility, and change-handling capabilities.

These results reinforce each other:

- SEM provided causal validation,
- TOPSIS ensured objective prioritization, and
- ANN enabled predictive validation.

Collectively, this triangulation affirms the construct validity and internal consistency of the proposed readiness model.

Table 14 - Alignment of Key Influencing Constructs Across Methods

Construct	SEM Impact on BN (β)	ANN Feature Weight	Present in TOPSIS High Scores (SAIL/GAIL)
Leadership (LD)	0.805	0.6434	✅ Yes
Agility (AG)	Not Significant	0.2440	✅ Yes
Change Handling (CH)	0.336 (indirect via HA)	0.2152	✅ Yes
Trust (TR)	-1.444 (inverse)	0.1660	✅ Yes
Human-AI (HA)	0.439	0.1338	❌ Moderate
Learning Culture (LC)	0.087	0.1877	❌ Mixed

5 DISCUSSION

The findings of this study contribute to the growing body of literature on supply chain readiness and digital transformation by offering both alignment and divergence from prior research. Consistent with Bag *et al.* (2021) and (Beuren *et al.*, 2023), these studies confirms that leadership dynamics is a pivotal enabler of SC transformation, underscoring the role of innovation-oriented leadership in enhancing responsiveness. Similarly, the positive yet moderate effect of human–AI collaboration resonates with Dwivedi (2019) and Sauer & Burggräf (2025), who highlighted the efficiency gains of hybrid intelligence, although our results suggest that such integration in Indian PSUs remains nascent compared to advanced digital firms. In contrast, the negative association of technological readiness with business network integration diverges from Al-Talib *et al.* (2020), (John *et al.*, 2024) and Modgil *et al.* (2022), who positioned IoT and AI adoption as primary enablers of supply chain resilience and transparency. This discrepancy may be attributed to contextual differences, as PSUs often face rigid bureaucratic processes and legacy infrastructure that constrain the benefits of technological upgrades. Furthermore, the limited predictive power of learning culture differs from Eryarsoy *et al.* (2022), who found organizational learning to be a catalyst for performance in education, suggesting sectoral variability in how learning translates into readiness. By situating these results within existing scholarship, the study demonstrates that while certain dimensions (leadership, agility) are universally critical, others (technology, learning culture) manifest differently across contexts, thereby enriching theoretical debates on SC5.0 adoption.

Table 15 - Summary of Hypotheses Testing and Cross-Method Validation

Code	Hypothesis	SEM Result (β, p-value)	ANN Weight (± SD)	TOPSIS Ranking Evidence	Status
H1	Technological readiness positively influences SC5.0 preparedness	β = -1.444 (p < 0.001) (Negative)	0.1660 ± 0.0545 (Low)	TR_Score not dominant	❌ Rejected
H2	Leadership commitment moderates SC5.0 outcomes	β = 0.805 (p < 0.001) (Strong +ve)	0.6434 ± 0.1674 (High)	SAIL, GAIL rank high on LD	✅ Accepted
H3	Digital skills and AI literacy predict SC5.0 readiness	β = 0.438 (p = 0.038) (Moderate +)	0.1338 ± 0.0498 (Lower)	HA_Score varies by PSU	✅ Accepted (Partially)
H4	Human-AI collaboration affects operational agility	β = -0.027 (p = 0.510) (NS)	0.2440 ± 0.0599 (Moderate)	No strong HA-AG link	❌ Rejected
H5	Learning culture mediates digital infra–implementation link	β = 0.087 (p = 0.336) (NS)	0.1877 ± 0.0456 (Low)	LC_Score low and insignificant	❌ Rejected

Importantly, the study confirms the convergence of findings across all three analytical approaches. Constructs such as leadership and agility were consistently identified as critical predictors across SEM (causal relationships), TOPSIS (decision rankings), and ANN (predictive modeling), adding robustness to the theoretical implications. The divergence of expected technological drivers (like TR and HA) challenges the deterministic assumption that digital tools alone ensure preparedness. Instead, this study contributes to emerging literature by emphasizing contextual maturity, human governance, and strategic leadership as central to SC5.0 transitions in complex public-sector ecosystems.

6 IMPLICATIONS

6.1 Theoretical Implications

This research makes a significant contribution to the evolving literature on Industry 5.0 and digital transformation within public sector environments by advancing a more nuanced understanding of supply chain readiness. It challenges the traditionally deterministic assumptions that place technological readiness at the center of transformation, instead revealing leadership commitment as a dominant causal and predictive factor in SC 5.0 adoption. By employing a robust multi-method analytical framework—integrating Structural Equation Modeling (SEM), TOPSIS, and Artificial Neural Networks (ANN)—the study demonstrates the methodological value of hybrid approaches in analyzing complex, multidimensional constructs such as SC 5.0 preparedness. Additionally, it highlights the latent limitations of AI integration and organizational learning culture, positioning these as critical barriers that must be addressed. In doing so, the research expands the socio-technical discourse in supply chain and organizational studies. Furthermore, it provides compelling empirical evidence against over-reliance on digital infrastructure alone, underscoring the necessity of strategic, human-centric governance mechanisms to drive meaningful transformation.9.2 Practical Implications.

6.2 Practical Implications

For policymakers, public sector administrators, and industry leaders, this study provides a strategic foundation for enabling the successful transition toward Supply Chain 5.0. First, it underscores the critical need to prioritize leadership development and strategic change management, recognizing these as foundational enablers of transformation rather than peripheral concerns. Second, it calls for a reassessment and modernization of technological infrastructure—moving beyond the mere expansion of digital assets to systems that dynamically align with evolving inter-organizational demands. Third, the research emphasizes targeted investment in AI literacy and continuous learning programs, particularly within lower-ranked PSUs, to bridge identified capability gaps. Fourthly, it advises that other units may profit from the agile governance practices and digital maturity of high-performing PSUs, such as SAIL and GAIL. Lastly, the paper suggests the use of advanced data-driven decision-support technologies like TOPSIS and ANN to improve readiness diagnostics, direct resource allocation, and encourage evidence-based performance benchmarking across the sector.

7 CONCLUSION

Artificial Neural Network (ANN), Multi-Criteria Decision Making (TOPSIS), and Structural Equation Modeling (SEM) were employed in this research to quantitatively analyze SC5.0 readiness across Indian Public Sector Units (PSUs). Seven latent constructs—Technological Readiness (TR), Human-AI Collaboration (HA), Agility (AG), Leadership Dynamics (LD), Learning Culture (LC), Change Handling (CH), and Business Network Integration (BN)—were identified through triangulation, offering prediction validation and comparative rankings. SEM analysis confirmed that leadership dynamics (LD → BN: $\beta = 0.805$, $p < 0.001$) was the strongest positive predictor of readiness, while technological readiness (TR → BN: $\beta = -1.444$, $p < 0.001$) had a significant negative association. Human–AI collaboration had a moderate but significant effect (HA → BN: $\beta = 0.439$, $p = 0.038$), whereas learning culture and agility were statistically insignificant. At the organizational level, TOPSIS revealed that SAIL (0.5223), GAIL (0.4991), and HAL (0.4650) ranked highest in SC5.0 readiness, while BEL (0.2733) lagged significantly. ANN validation achieved $R^2 = 0.8841$ with RMSE = 0.0211, confirming predictive robustness and highlighting leadership (weight = 0.6434) and agility (weight = 0.2440) as the most influential features. Collectively, these results demonstrate that although Indian PSUs are progressing toward SC5.0, readiness is highly uneven across units, with leadership emerging as the pivotal driver. The rejection of hypotheses H1, H4, and H5, alongside the partial acceptance of H3, indicates that socio-technical integration is still nascent, particularly in terms of workforce digital literacy and organizational learning. The study provides a quantitatively grounded, multidimensional picture of SC5.0 adoption, offering both theoretical clarity and practical pathways for transformation.

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