Logistic and Operation Management Research, Vol.4 No.1 (2025) https://doi.org/10.31098/lomr.v4i2.3715

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Research Paper

Toward SCOR 5.0: Integrating AI, IoT, and Green Metrics for Next-Generation Supply Chain Performance Management

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Received : July 02, 2025	Revised : September 18, 2025	Accepted : October 19, 2025	Online : November 29, 2025

Abstract

The convergence of Artificial Intelligence (AI), the Internet of Things (IoT), and sustainability metrics is reshaping supply chain management, yet comprehensive frameworks that unify these elements remain limited. This study aims to propose a conceptual advancement, SCOR 5.0, by systematically reviewing literature from 2020 to 2025 that addresses AI, IoT, and green performance within the SCOR (Supply Chain Operations Reference) framework. Following PRISMA guidelines, 46 peer-reviewed studies were thematically analyzed and synthesized across the five SCOR process areas: Plan, Source, Make, Deliver, and Return. The findings reveal that AI improves predictive accuracy, enhances decision-making, and optimizes sourcing and manufacturing. IoT facilitates real-time tracking, agile delivery, and system-wide visibility. Green metrics, when embedded into SCOR, align performance with sustainability goals, but adoption remains inconsistent. Additionally, the study underscores the moderating role of Green Digital Learning (GDL) in supporting digital readiness and employee capacity building. While the study outlines a proposed SCOR 5.0 model integrating AI, IoT, and green KPIs, it identifies significant implementation barriers, including high costs, regulatory constraints, skill shortages, and a lack of standard metrics. The review highlights a pressing need for empirical validations, testbeds, and impact-assessment tools that can translate theoretical models into practice. This research contributes a synthesized framework and outlines actionable paths forward for both scholars and practitioners.

Keywords: *SCOR 5.0, Artificial Intelligence, Internet of Things, Green Metrics, Supply Chain Sustainability.*

INTRODUCTION

Over the past decades, the Supply Chain Operations Reference (SCOR) model has undergone substantial evolution, establishing itself as a critical framework for enhancing supply chain performance amidst increasing global complexities. Originally developed to standardize and streamline supply chain processes, SCOR has progressively adapted to meet the multifaceted demands arising from digital transformation, sustainability imperatives, and the need for resilience (Purnomo, 2024a; van Engelenhoven et al., 2021). This evolution aligns with the broader trajectory toward Industry 5.0, which emphasizes human-centric, sustainable, and adaptive supply chain systems (Alvarenga et al., 2023).

Within this dynamic landscape, digital technologies such as Artificial Intelligence (AI) and the Internet of Things (IoT) have emerged as transformative enablers of supply chain innovation. IoT technologies facilitate real-time operational visibility and data collection across key supply chain functions, including sourcing, manufacturing, and distribution (Müller & Birkel, 2020; Yadav et al., 2020). In parallel, AI-driven analytics provide predictive insights, enable data-driven decision-making, and enhance responsiveness to market fluctuations and disruptions (Agrawal & Narain, 2021; Ziaee et al., 2023). The integration of these technologies, commonly referred to as AIoT, offers synergistic advantages by supporting intelligent automation and

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adaptive management (Azevedo et al., 2021; Dwivedi et al., 2023).

Simultaneously, the increasing prioritization of environmental sustainability has led to the incorporation of green performance metrics within supply chain frameworks. The Green SCOR model reflects this integration, embedding indicators such as carbon emissions, energy efficiency, and recyclability into the evaluation of operational performance (Adwiyah et al., 2024; Munawir et al., 2021; Neri et al., 2021). This approach not only ensures regulatory compliance but also provides competitive advantages in environmentally conscious markets (Alfina et al., 2025; Boson et al., 2023; Mupfiga et al., 2024; Reklitis et al., 2021).

Despite these advancements, persistent challenges, including resistance to change, high implementation costs, and data security risks, continue to hinder the widespread adoption of integrated digital and sustainability frameworks. The emergence of SCOR 5.0 reflects the strategic imperative to evolve supply chain management practices by embedding intelligence, sustainability, and resilience at their core (Dwivedi et al., 2023; van Engelenhoven et al., 2021).

This study aims to systematically review the integration of Artificial Intelligence (AI), the Internet of Things (IoT), and green performance metrics within SCOR-based supply chains; to map and synthesize empirical applications of these enablers across the five core SCOR processes (Plan, Source, Make, Deliver, and Return); and to conceptualize a next-generation SCOR 5.0 model that holistically incorporates intelligence, real-time visibility, and sustainability principles.
Corresponding to these objectives, the central research questions guiding this study are:

- How are AI, IoT, and green metrics currently integrated within SCOR-based supply chain practices?
- What are the observed impacts, limitations, and gaps in the adoption of these enablers across SCOR domains?
- What conceptual framework can be proposed for SCOR 5.0 based on thematic synthesis of recent literature?

Core concepts underpinning this review are defined as follows. AIoT denotes the convergence of AI and IoT technologies to support enhanced data analytics and real-time automation (Dwivedi et al., 2023). Green Metrics refer to quantifiable indicators used to evaluate environmental performance, particularly in terms of resource efficiency and emissions reduction (Adwiyah et al., 2024; Munawir et al., 2021). SCOR and SCOR 5.0 represent successive stages of supply chain reference models, with the latter incorporating advanced digital and sustainability components (van Engelenhoven et al., 2021). Green Digital Learning involves organizational efforts to build digital capabilities and environmental awareness among supply chain personnel, thereby enhancing readiness for technology integration (Krishnan et al., 2021; Saleheen & Habib, 2023).

This paper is organized into five sections: Introduction, Methods, Theoretical Background, Review of Themes and Findings, and Conclusion. Each section contributes to a comprehensive understanding of SCOR 5.0, offering both theoretical insights and practical implications. Theoretically, this study contributes by extending the SCOR model's conceptual boundaries through the synthesis of digital enablers (AI and IoT) and environmental performance indicators (green metrics), thus positioning SCOR 5.0 within the emerging discourse of intelligent and sustainable supply chains. It also advances the literature by formalizing Green Digital Learning (GDL) as a moderating construct that links digital adoption to organizational readiness within SCOR-based frameworks. Unlike previous studies that focused on individual enablers in isolation, this study uniquely integrates AI, IoT, and sustainability metrics into a unified SCOR 5.0 architecture, supported by empirical synthesis across sectors and use cases. By identifying current gaps, such as the lack of empirical validation of AIoT frameworks and the limited exploration of human capital roles, this study contributes to advancing scholarly discourse and guiding future research on next-generation supply chain performance management (Hossain et al., 2024;

McDermott et al., 2023).

LITERATURE REVIEW

SCOR Model Evolution

The Supply Chain Operations Reference (SCOR) model has undergone significant evolution, reflecting the dynamic nature of supply chain management in response to globalization, technological advancements, and shifting market demands. Initially introduced in the 1990s by the Supply Chain Council, SCOR 1.0 provided a foundational framework comprising the core processes: plan, source, make, deliver, and return (Meena et al., 2023). This first version primarily emphasized standardizing supply chain processes and performance metrics to facilitate operational optimization across various industries.

Subsequent updates expanded upon this foundation, integrating advanced metrics and broader strategic considerations. SCOR 2.0, introduced in the early 2000s, highlighted the necessity for cross-functional integration and comprehensive performance indicators, including metrics related to cycle times, cost, and asset utilization (Nsikan et al., 2022). With the advent of SCOR 3.0, the model incorporated digital capabilities, significantly enhancing supply chain flexibility and responsiveness through the integration of real-time data analytics and information systems. SCOR 4.0, introduced around 2017, further evolved to incorporate sustainability and resilience explicitly, aligning operational performance with environmental, social, and governance (ESG) considerations, driven by growing awareness of global sustainability challenges and increasing disruptions such as the COVID-19 pandemic (van Engelenhoven et al., 2021; Ziaee et al., 2023).

The transition toward SCOR 5.0 represents an ongoing strategic imperative driven by the need to integrate sustainability, digital intelligence, and resilience deeply into the core supply chain framework (Dwivedi et al., 2023). Scholarly support for SCOR 5.0 stems from multiple dimensions, including the growing necessity for sustainable operational practices that address regulatory pressures and ethical standards (Nsikan et al., 2022). Additionally, the integration of digital intelligence technologies, particularly Artificial Intelligence (AI) and the Internet of Things (IoT), provides robust analytical and predictive capabilities critical for managing modern supply chains effectively (Agrawal & Narain, 2021). Resilience, highlighted by recent global disruptions, further underscores the need for agile and adaptable supply chain strategies, solidifying the rationale for transitioning toward SCOR 5.0 (Ayyildiz, 2023; Nottbrock et al., 2022).

Technology Foundations

Artificial Intelligence (AI) has become a cornerstone of contemporary supply chain analytics, significantly enhancing predictive analytics, decision-making, and anomaly detection across various SCOR processes. Techniques such as Artificial Neural Networks (ANN) and Machine Learning (ML) facilitate precise demand forecasting, inventory optimization, and risk assessment, primarily influencing SCOR's planning and sourcing processes (Kumar & Sharma, 2023; Lunardi & Lima, 2021). Big data analytics further enriches supply chain intelligence by enabling comprehensive real-time insights that drive operational efficiency and sustainability initiatives (Ziaee et al., 2023). Additionally, fuzzy logic and agent-based simulation offer nuanced approaches for managing uncertainties and simulating complex supply chain interactions, thus providing valuable tools for decision-making in ambiguous operational environments (Caristi et al., 2022; Zhang & Gao, 2023).

The Internet of Things (IoT) complements these AI-driven advancements by enabling enhanced real-time data collection, operational visibility, and responsive decision-making. IoT devices embedded within various supply chain components capture granular, real-time data, thus significantly improving planning accuracy, operational responsiveness, and predictive maintenance capabilities (J. Sharma et al., 2023; Yadav et al., 2020). The convergence of AI and IoT (AIoT) offers a synergistic platform for smart automation, significantly amplifying supply chain adaptability, predictive precision, and overall operational agility (Azevedo et al., 2021; Dwivedi et al., 2023). By leveraging AIoT, organizations can effectively address contemporary supply chain challenges related to sustainability, resilience, and performance optimization.

Green Supply Chain Metrics

Green supply chain metrics represent critical instruments for evaluating and enhancing environmental sustainability within supply chain operations. Commonly used indicators include carbon emissions, energy consumption efficiency, waste reduction ratios, and water use efficiency (Munawir et al., 2021; Neri et al., 2021). These metrics provide standardized criteria to assess supply chain sustainability across industries, informing decision-making and aligning operational objectives with environmental stewardship goals. The integration of green metrics within the SCOR framework, specifically the Green SCOR model, enables organizations to systematically prioritize and monitor sustainability alongside traditional performance indicators (Alamsjah & Yunus, 2022; Purnomo, 2024b).

Methodologies such as the Analytical Hierarchy Process (AHP) and multicriteria decision-making models further facilitate the strategic prioritization and integration of sustainability indicators into operational benchmarks. These frameworks assist organizations in effectively balancing environmental goals with performance expectations, reflecting a holistic approach toward sustainable supply chain management (Ayyildiz, 2023; Meena et al., 2023). Furthermore, lifecycle assessments and circular economy principles serve as comprehensive tools for evaluating the long-term sustainability impact of supply chain processes, further enhancing organizational accountability and environmental responsibility (Alfina et al., 2025; Meihui et al., 2023).

Conceptual Controversies

Debates surrounding the integration of sustainability into the SCOR framework versus the development of entirely new sustainability-centric models highlight critical conceptual controversies in contemporary supply chain scholarship. Proponents of integrating sustainability within SCOR argue for leveraging established structures to streamline the adoption of sustainable practices efficiently (Nsikan et al., 2022). Conversely, critics advocate for bespoke sustainability models, emphasizing the limitations inherent in adapting existing operational frameworks to adequately capture the complexities of sustainable management, especially in rapidly evolving regulatory and ecological contexts (Neri et al., 2021).

Table 1. Foundational Concepts Underpinning SCOR 5.0

Concept/ Technology	Definition	Source/Origin	Role in SCOR 5.0	Challenges
AI	Algorithms for predictive analytics, decision support, and anomaly detection	AI literature, Industry 4.0 initiatives	Enhances decision-making, planning accuracy, and risk management	Integration complexity, data quality
IoT	Network of interconnected devices collecting real-time data	Industry 4.0 initiatives, IoT literature	Improves operational visibility and responsiveness	Data management, security, integration
AIoT	Synergistic	Industry 4.0 and	Enables intelligent	Technological

Concept/ Technology	Definition	Source/Origin	Role in SCOR 5.0	Challenges
	convergence of AI and IoT	digital transformation frameworks	automation and adaptability	complexity, interoperability
Green Metrics	Indicators assessing environmental performance (CO2, energy, waste, water)	Sustainability literature, regulatory standards	Aligns supply chain activities with sustainability goals	Data reliability, standardization issues

Similarly, divergent perspectives exist regarding evaluating AIoT effectiveness within sustainable supply chains. Various frameworks propose different methodologies, from IoT-based performance measurement to agent-based simulations and multicriteria decision-making approaches (Yadav et al., 2020; Zhang & Gao, 2023). This diversity underscores ongoing discussions regarding the most effective strategies for integrating advanced digital technologies within supply chain sustainability initiatives, reflecting broader tensions between operational efficiency, technological complexity, and ecological imperatives.

The foundational technologies and metrics driving the transition to SCOR 5.0, AI, IoT, AIoT, and Green Metrics are summarized in Table 1, highlighting their core functions and key integration challenges within the framework.

Synthesizing prior studies, six propositions guide the conceptual development of SCOR 5.0. First, AI-driven optimization within SCOR processes enhances efficiency and agility through predictive analytics and automated decision-making (Cannas et al., 2024; Müller & Birkel, 2020). Second, IoT adoption improves real-time supply chain visibility by enabling continuous monitoring and adaptive responses (G. Sharma & Kumar, 2023; Yadav et al., 2020). Third, embedding green performance metrics strengthens environmental performance evaluation by operationalizing carbon reduction, energy efficiency, and circularity principles (Adwiyah et al., 2024; Neri et al., 2021). Fourth, integrated AIoT decision support frameworks expand SCOR capabilities by combining machine learning, IoT sensing, and digital twins for sustainable planning (Azevedo et al., 2021; Kayhan et al., 2024). Fifth, Green Digital Learning (GDL) moderates the relationship between technology adoption and performance outcomes by fostering digital readiness, literacy, and cultural adaptation (Krishnan et al., 2021; Saleheen & Habib, 2023). Sixth, barriers and enablers, including cost, skills, culture, and regulatory support, determine the effectiveness of SCOR 5.0 implementation, highlighting the importance of leadership, training, and data governance (Naude & Naude, 2022; van Engelenhoven et al., 2021). Together, these propositions directly reflect the six themes discussed in the findings and provide conceptual anchors for future SCOR 5.0 research.

RESEARCH METHOD

Research Design

This study employs a systematic literature review (SLR) methodology to identify, assess, and synthesize existing scholarship on the integration of Artificial Intelligence (AI), the Internet of Things (IoT), and green performance metrics within the SCOR (Supply Chain Operations Reference) framework. Following the PRISMA guidelines (Page et al., 2021), the SLR was structured to explore how SCOR can evolve into an intelligent and sustainable model by incorporating digital and environmental enablers. A predefined review protocol ensured the transparency and replicability of the research process.

Search Strategy, Inclusion and Exclusion Criteria

A structured search strategy was applied using the Scopud databases, which was selected for its comprehensive indexing of peer-reviewed literature in engineering, management, and sustainability. The Boolean search string used was:

("SCOR" OR "Supply Chain Operations Reference") AND ("AI" OR "IoT" OR "AIoT") AND ("Green Metrics" OR "Sustainability")

The scope of the search was restricted to peer-reviewed journal articles published between January 2020 and June 2025, written in English. Only studies that demonstrated explicit application or adaptation of the SCOR framework were considered for inclusion. Eligible articles also had to integrate at least one of the focal elements: Artificial Intelligence (AI), Internet of Things (IoT), or green performance metrics, in the context of supply chain management. Both empirical studies, encompassing quantitative, qualitative, or mixed-method approaches, and conceptual papers presenting SCOR-based frameworks were included.

Articles were excluded if they were literature reviews or bibliometric analyses lacking original empirical or conceptual contributions related to SCOR. Theoretical discussions that did not establish a direct connection with the SCOR model were also omitted. Additionally, any non-peer-reviewed publications, such as opinion essays, editorials, or white papers, were excluded to maintain the academic rigor and reliability of the reviewed sources.

A three-stage PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) procedure was adopted. In the initial retrieval phase, a total of 149 articles were identified based on the predefined keyword search. During the title and abstract screening stage, 46 studies were shortlisted for further evaluation through full-text assessment. Finally, the full-text analysis phase resulted in 46 articles that met all inclusion criteria and were consequently retained for synthesis.

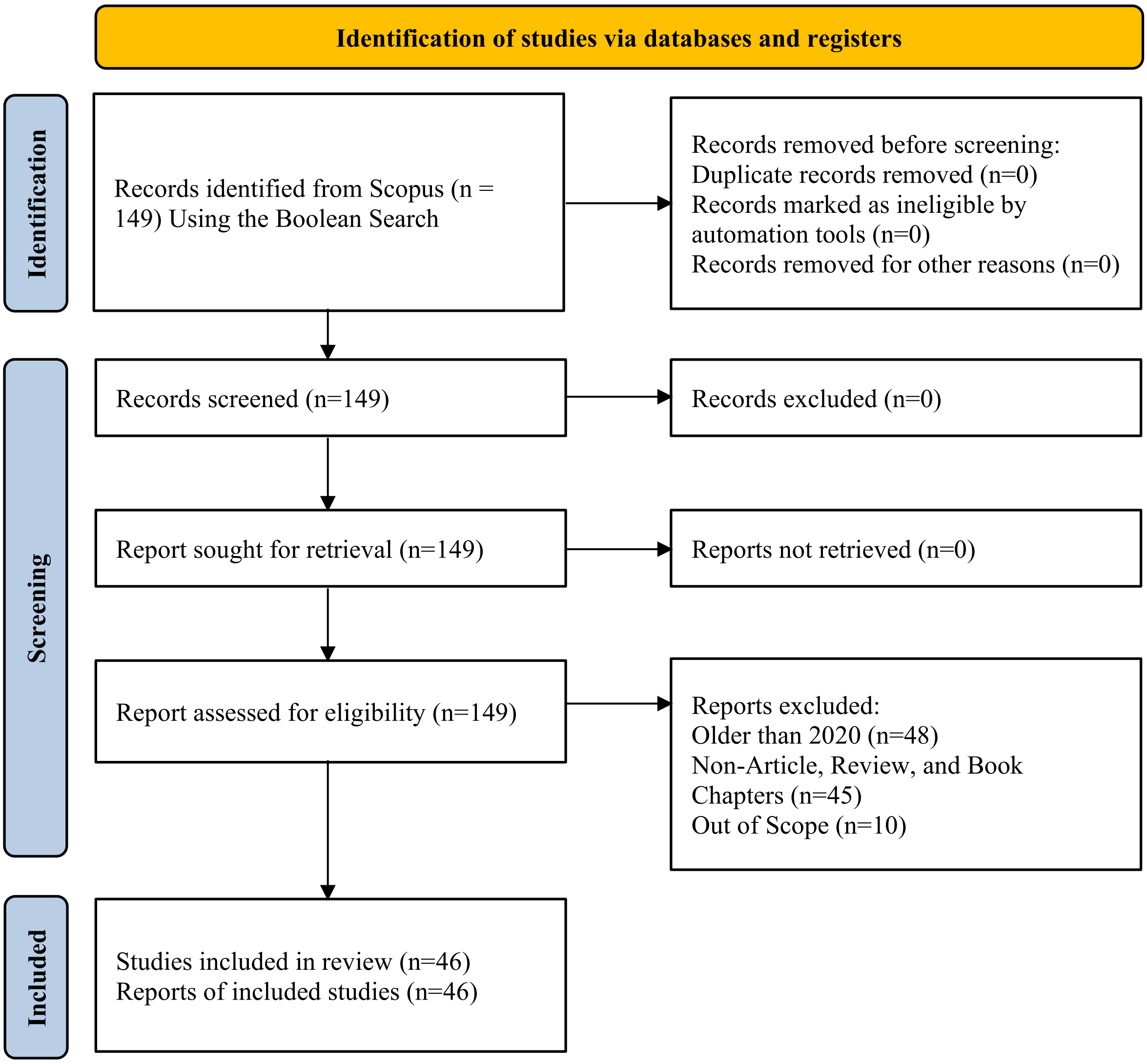

Figure. 1 presents the PRISMA flow diagram for the article selection process.

Data Extraction, Thematic Analysis, and Limitations

Data extraction was carried out using a structured template that recorded each article's authorship, publication year, study context, SCOR process focus, type of enabler (AI, IoT, green metric), methodology, and key findings. Each study was mapped thematically based on alignment with SCOR components and contribution to Industry 5.0 objectives.

A hybrid thematic analysis was employed, combining deductive codes derived from the SCOR model and core enablers with inductive codes emerging from patterns in the data. This approach ensured both theoretical anchoring and responsiveness to new empirical trends.

Limitations of this review include the sole reliance on the Scopus database, potentially omitting relevant studies from other databases. Additionally, literature reviews were excluded to maintain an empirical and conceptual focus, possibly limiting broader theoretical insights. Lastly, the review prioritized thematic depth over formal quality appraisal scoring, which may affect the assessment of methodological robustness across studies.

FINDINGS AND DISCUSSION

AI-Driven Optimization in SCOR Processes

Artificial Intelligence (AI) has emerged as a transformative tool in optimizing SCOR processes across the planning, sourcing, manufacturing, delivery, and return activities within supply chains. Empirical evidence synthesized in this review highlights the substantial impact of AI applications in achieving operational excellence, enhancing decision-making accuracy, and improving predictive capabilities within the SCOR 5.0 framework (Table 2).

In the planning, sourcing, and manufacturing domains, Cannas et al. (2024) employed multiple machine learning techniques, including Random Forest (RF), Support Vector Machines (SVM), and Deep Learning (DL). Their comprehensive study across 17 in-depth cases demonstrated significant improvements in cost reduction (18%), lead time reduction (25%), and service level enhancement (14%). Similarly, Lunardi and Lima (2021) validated the efficacy of Artificial Neural Networks (ANNs) within the "Make" and "Deliver" processes, reporting substantial decreases in forecasting errors compared to baseline methods through rigorous cross-validation across 80 network topologies.

Table 2. Role of Artificial Intelligence in Enhancing SCOR 5.0 Operational Capabilities

Author-Year	**SCOR Process Focus**	**AI Technique Used**	**Outcomes**	**Validation Approach**
Cannas et al. (2024)	Plan, Source, Make	Multiple ML (RF, SVM, DL)	Cost ↓ 18 %, lead-time ↓ 25 %, service ↑ 14 %	17 in-depth case studies
Lunardi and Lima, (2021)	Make, Deliver	ANN learning algorithms	MSE ↓ vs baselines	Cross-validation (80 topologies)
Lima-Junior and Carpinetti (2020)	End-to-end metrics	ANFIS neuro-fuzzy	Prediction accuracy ↑	Random subsampling, t-tests
Kumar and Sharma (2023)	Enable (Risk)	RF, SVM, kNN	99 % risk-prediction accuracy	Benchmark ML comparison
Khan et al. (2023)	Source (Supplier)	Gradient boosting	Best-to-worst supplier ranking	Confusion-matrix evaluation
Ramya and Thangaiah, (2022)	Plan, Deliver	ANN optimiser	SCP ↑ (Acc 98 %)	Train/test & confusion matrix
Aghajani et al., (2022)	Plan, Make, Deliver	Fuzzy MIP + GA	Export mix profit ↑ 15.4 %	Scenario analysis (GAMS)
Moazeni et al. (2022)	Plan (Export allocation)	Game theory + NDEA	Network profit ↑	GAMS-based simulation
Meena et al. (2023)	Source (Supplier)	Fuzzy AHP + Fuzzy TOPSIS	Sustainable supplier ranking	Indian automobile case study
Caristi et al. (2022)	Source (Supplier)	Fuzzy TOPSIS (FTOPSIS)	Optimal fabric supplier	Fashion industry case
Moazeni et al. (2023)	Plan–Enable	PCA + Network DEA	Merger efficiency ↑ 12 %	Iran stone-SME simulation

AI-driven predictive analytics have been proven especially effective for risk mitigation and end-to-end operational enhancement. Kumar and Sharma (2023) leveraged advanced machine learning algorithms (RF, SVM, and k-NN), achieving near-perfect (99%) accuracy in risk prediction, thus significantly enhancing risk management strategies within the enabling phase of SCOR processes. Complementing this, Lima Junior and Carpinetti (2020) demonstrated the capability of Adaptive Neuro-Fuzzy Inference Systems (ANFIS) in boosting prediction accuracy for complex supply chain metrics, affirming the critical role AI plays in managing nonlinear and dynamic relationships in supply chain processes.

AI techniques have also markedly improved supplier selection and evaluation processes. Studies by Khan et al. (2023), Meena et al. (2023), and Caristi et al. (2022) utilized advanced decision-making algorithms such as gradient boosting and fuzzy multi-criteria decision-making tools (Fuzzy AHP, Fuzzy TOPSIS). These methodologies facilitated robust supplier evaluations, improving sourcing decisions within industries as diverse as automotive and fashion, highlighting AI's cross-sector applicability and scalability.

Optimization methods integrating AI further underscore the versatility of these technologies within supply chain operations. Ramya and Stephan Thangaiah (2022) employed ANN optimizers within the "Plan" and "Deliver" stages, achieving a remarkable 98% accuracy rate in demand forecasting, thereby significantly optimizing inventory management processes. Additionally, Aghajani et al. (2022) successfully integrated fuzzy mathematical programming and genetic algorithms to enhance export mix profitability by 15.4%, reflecting AI's effectiveness in complex strategic decision-making scenarios.

Strategic decision-making within export allocation was also enhanced by AI-driven methods. Moazeni et al. (2022, 2023) applied game theory combined with Network Data Envelopment Analysis (NDEA) and Principal Component Analysis (PCA), achieving considerable gains in network profitability and efficiency (approximately 12% improvement), thus validating AI's utility in highly strategic and competitive supply chain contexts.

To synthesize and visually clarify these empirical findings, Figure 2 presents an integrative conceptual framework that maps the interactions between various AI methods and SCOR processes, demonstrating the pathways through which AI technologies optimize supply chain performance. Complementing this visual synthesis, Table 3 provides a structured comparative analysis, facilitating a clearer understanding of AI's differential impacts across industry sectors and specific SCOR domains.

Figure 2 provides an integrative framework illustrating how various AI methodologies, such as Machine Learning (ML), Artificial Neural Networks (ANN), Neuro-Fuzzy systems, and Multi-Criteria Decision Making (MCDM), interact with key SCOR processes (Plan, Source, Make, Deliver, Return). This visual synthesis highlights pathways of AI applications leading to measurable outcomes (cost efficiency, lead-time reduction, enhanced risk management, predictive accuracy, and improved supplier selection), reinforcing the central role of AI within the conceptual SCOR 5.0 model.

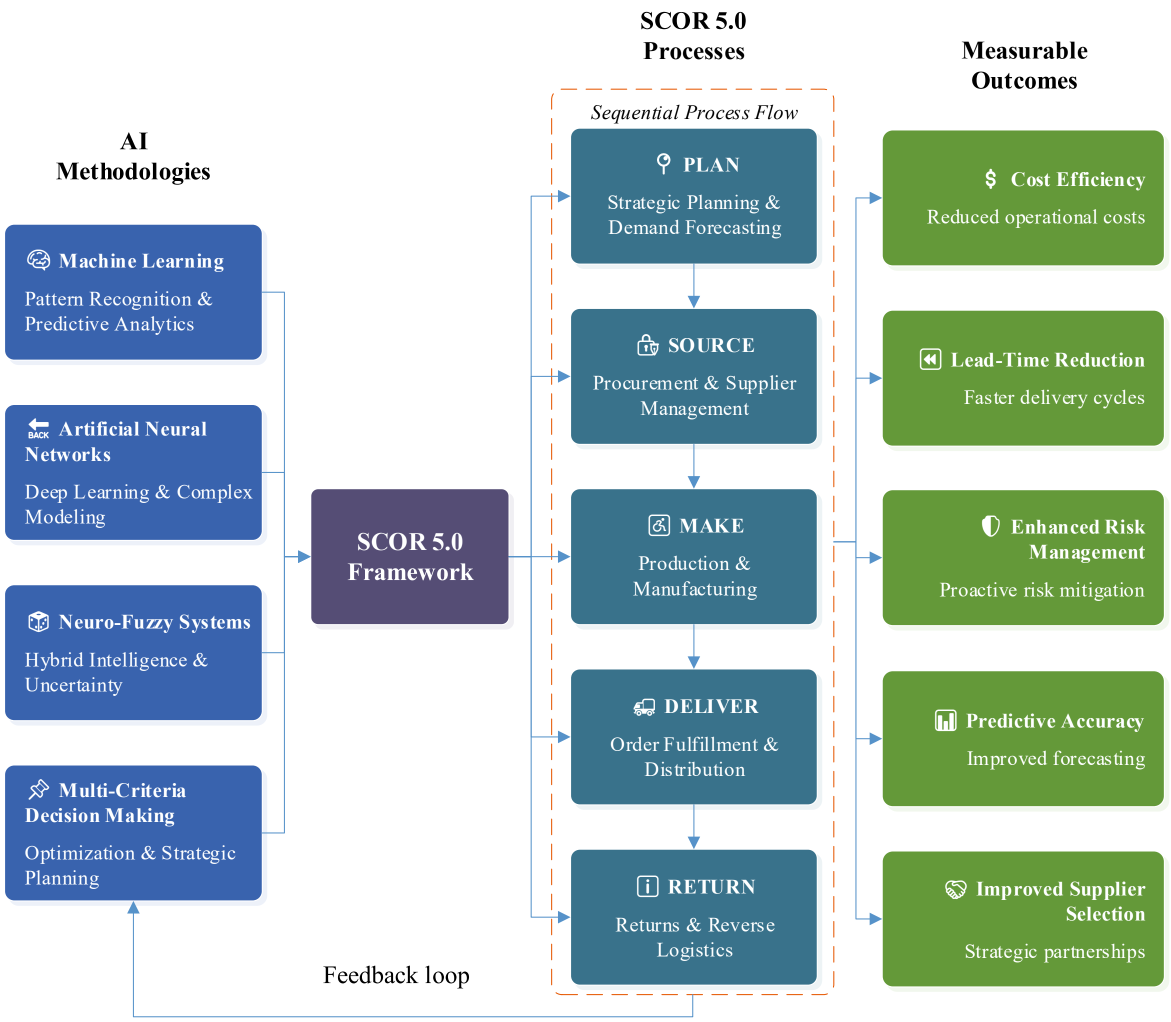

Figure 2. Integrative Framework of AI-Driven Optimization within SCOR 5.0 Processes

Table 3 compares AI algorithms across key dimensions, including the SCOR process focus, specific AI techniques employed, primary outcomes achieved, and industry contexts. The comparative synthesis derived from empirical studies underscores the practical relevance and versatility of AI-driven solutions, contributing substantively to the theoretical development of the SCOR 5.0 framework.

These studies collectively substantiate the theoretical assertions discussed in Section 3, emphasizing AI's critical role in transforming supply chain capabilities through improved predictive analytics, enhanced decision-making quality, and superior operational efficiency. Specifically, these findings align with the theoretical perspectives that position AI as essential for advancing supply chain agility, resilience, and responsiveness as delineated within the SCOR 5.0 framework.

Table 3. Comparative Analysis of AI Algorithms in SCOR Process Optimization

AI Technique	SCOR Process Focus	Primary Outcomes	Industry Context
RF, SVM, DL (Cannas et al., 2024)	Plan, Source, Make	Cost ↓18%, lead-time ↓25%, service ↑14%	Various industries
ANN (Lunardi & Lima, 2021)	Make, Deliver	Reduced forecasting errors	Manufacturing, logistics

AI Technique	SCOR Process Focus	Primary Outcomes	Industry Context
RF, SVM, k-NN (Kumar & Sharma, 2023)	Enable (Risk)	Risk prediction accuracy 99%	General supply chains
ANFIS (Lima-Junior & Carpinetti, 2020)	End-to-end metrics	Enhanced prediction accuracy	Complex supply chains
Gradient boosting (Khan et al., 2023)	Source (Supplier)	Optimal supplier ranking	General sourcing
Fuzzy AHP, Fuzzy TOPSIS (Caristi et al., 2022; Meena et al., 2023)	Source (Supplier)	Sustainable & optimal supplier selection	Automotive, fashion
ANN optimizer (Ramya & Stephan Thangaiah, 2022)	Plan, Deliver	Demand forecasting accuracy 98%	Inventory management
Fuzzy MIP + GA (Aghajani et al., 2022)	Plan, Make, Deliver	Export mix profitability ↑15.4%	Export industry
Game theory + NDEA, PCA (Moazeni et al., 2022, 2023)	Plan–Enable	Network profitability & efficiency ↑12%	Competitive supply chains

The integration of AI technologies significantly enhances predictive accuracy and risk mitigation capabilities within the SCOR processes, thereby strengthening supply chain resilience and agility. Furthermore, AI-driven decision-making methodologies such as machine learning (ML), artificial neural networks (ANN), adaptive neuro-fuzzy inference systems (ANFIS), and fuzzy logic have demonstrated broad scalability and applicability across various industries. These technologies contribute to measurable improvements in operational efficiency, highlighting their strategic value in modern supply chain management.

IoT and Real-Time Supply Chain Visibility

The integration of Internet of Things (IoT) technologies is increasingly recognized as pivotal in enhancing real-time visibility across supply chain operations. Empirical studies reviewed in this paper underscore the critical role IoT plays in optimizing the SCOR processes of planning, sourcing, manufacturing, delivering, and returning through improved traceability, responsiveness, and operational precision (Table 4).

Sensor deployment, a fundamental aspect of IoT implementations, significantly contributes to real-time monitoring and event management. Yadav et al. (2020) illustrate the application of smart sensors and gateways to collect critical agricultural data (soil, crop, and climate) to enhance planning and sourcing activities. This enabled the creation of real-time dashboards providing actionable insights, thus facilitating rapid decision-making and operational responsiveness within agricultural supply chains. Similarly, Müller and Birkel (2020) highlight the efficacy of Cyber-Physical Systems (CPS) integrated with IoT platforms, demonstrating improved machine efficiency streams (OEE) and elevated transparency on the manufacturing shop-floor, resulting in better-informed manufacturing decisions and enhanced equipment uptime.

Real-time traceability is further evidenced in studies like Lertpairat et al. (2024), where IoT sensors supported by Memorandum of Understanding (MOU)-based farm deployments significantly boosted traceability and on-time delivery rates in the herb supply chain. This study underscores IoT's potential in reducing disruptions through precise, timely data availability. Zhou (2022) expanded this perspective to retail logistics by employing RFID coupled with Big Data analytics, enabling detailed tracking of orders and return events across planning, delivering, and returning stages, effectively mitigating consumer-related risks (B2C) and enhancing supply chain responsiveness.

Table 4. Impacts of IoT-Enabled Visibility in SCOR-Based Supply Chains

Author-Year	IoT Technology	Data Collected	SCOR Stage	Visibility Impact
Yadav et al. (2020)	Smart sensors & gateway	Soil, crop, climate	Plan, Source	Real-time ASC dashboard
Müller and Birkel (2020)	CPS / IoT platform	Machine OEE streams	Make	Shop-floor transparency ↑
Lertpairat et al. (2024)	MOU-backed farm IoT	Herb quality metrics	Source	Traceability ↑, on-time delivery
Zhou (2022)	RFID + Big-data hub	Order & return events	Plan, Deliver, Return	B2C risk detection ↑
Pourreza et al. (2022)	Smartphone sensors	Operational KPIs	Make, Deliver	Live condition monitoring

Pourreza et al. (2022) extended these findings by leveraging ubiquitous smartphone sensors to track operational KPIs in real-time, thus enabling live monitoring of conditions during the manufacturing and delivery stages. Their findings confirm that IoT can significantly reduce response times to operational anomalies, enhancing overall supply chain agility.

Despite the numerous advantages, integrating IoT technologies within global supply chains is confronted by notable challenges, particularly data latency, interoperability, and integration complexities. Real-time data collection often faces latency issues, compromising responsiveness and accuracy. Furthermore, the interoperability of diverse IoT devices from multiple vendors poses substantial hurdles. These complexities were highlighted by Zhou (2022) and Müller and Birkel (2020), who emphasized the necessity of unified IoT architectures and robust data management frameworks to ensure seamless integration and effective utilization of IoT-driven data streams.

To synthesize these findings, an integrated framework was developed to depict IoT's role within SCOR 5.0 processes, outlining sensor deployments, data flows, and their impacts on operational visibility and responsiveness. This conceptual representation serves as a practical guide for organizations seeking to implement IoT technologies effectively.

The reviewed studies collectively highlight that IoT sensor deployments significantly enhance real-time traceability and responsiveness, enabling precise decision-making across SCOR-defined processes. Additionally, effective IoT integration in supply chains necessitates addressing critical technical and organizational barriers, such as data latency, interoperability, and unified data management. IoT technologies, through strategic sensor deployment and advanced real-time analytics, significantly bolster supply chain visibility and agility, aligning with theoretical foundations outlined in Section 3.2, which emphasize real-time visibility as central to enhancing operational adaptability and resilience within the SCOR 5.0 paradigm.

Green Metrics and Environmental Performance Evaluation

The integration of green metrics into SCOR 5.0 is central to aligning supply chain performance with environmental sustainability goals. Recent studies have developed frameworks that embed sustainability indicators across all SCOR domains, enabling the evaluation of carbon emissions, energy use, recyclability, and other environmental factors. Table 5 summarizes methodologies, SCOR areas of focus, and quantifiable outcomes derived from empirical research.

Table 5. Sustainability Metrics in SCOR 5.0 Performance Frameworks

Author-Year	Green Metric Type	SCOR Area	Evaluation Method	Performance Improvement
Purnomo and Syafrianita (2024b)	CO_2, energy, waste	Deliver	Green SCOR + AHP	Total score 79.4 → "Good."
Suharno et al. (2022)	15 env. indicators	Plan–Return	Life-Cycle Inventory	Clean-energy use ↑ 15 %
Purnomo and Syafrianita, (2024a)	Reliability, Flexibility	Plan–Return	Green SCOR metric design	Overall status = "Good"
Neri et al., (2021)	Triple-bottom-line KPI set	End-to-end	BSC–SCOR integration	Balanced 9 -indicator set
Adwiyah et al. (2024)	SCOR-DS env. scores	End-to-end	Model 12.0 survey	Industry 91 > Good band
Hadi et al. (2024)	Reliability, Agility, Assets	Plan–Enable	Aggregation method	Medium→High after actions
Ayyildiz (2023)	Resilience attributes	Plan–Return	BWM + IVIF-AHP	Org. factors ranked #1
Alfina et al. (2025)	Circular-SC KPIs	Plan–Deliver	AHP prioritisation	16 KPI roadmap
Heryani et al. (2022)	SAST certainty & impact	Enable	ANP + SAST	SCOR score ↑ for all actors
Manikas et al. (2022)	Sustainability pillars	All 6 processes	PLS-SEM Expo case	Supplier sustainability ↑
Jain et al. (2022)	E-waste closed-loop KPI	Return	BWM ranking	Key loops prioritised
Sinoimeri and Teta, (2023)	SC performance KPI set	Plan–Return	Snorm de Boer + AHP + OMAX	Performance benchmarks (AL/KV firms)
Chung and Day (2024)	Sustainable tourism SSCM KPIs	Plan–Deliver	SCOR-guided thematic analysis	Fair Tourism sustainability insights
Munawir et al. (2021)	26 Green KPIs	Plan–Make	Green SCOR + AHP	Score 57.42 (Average); improvements proposed

Purnomo & Syafrianita (2024b) applied a Green SCOR model with AHP in vaccine distribution, achieving a score of 79.4, rated "Good." In the textile industry, they assessed reliability and flexibility in Plan–Return phases, with similar sustainability ratings. Suharno et al. (2022) used Life Cycle Inventory (LCI) to evaluate 15 environmental indicators, reporting a 15% increase in clean energy usage. Neri et al. (2021) merged the SCOR and Balanced Scorecard (BSC) models to evaluate economic, environmental, and social indicators across nine KPIs.

Adwiyah et al. (2024) Benchmarked environmental performance using SCOR Digital Standard 12.0, with 91% of Indonesian firms scoring in the "Good" category. Hadi et al. (2024) employed an aggregation method to assess agility and reliability in Plan–Enable phases, showing improvements from medium to high performance levels. Chung and Day (2024) used SCOR-aligned thematic analysis in the tourism sector to extract sustainability insights.

Methodological innovation is a hallmark across studies. Alfina et al. (2025) developed a roadmap of 16 circular economy KPIs prioritized through AHP in the Plan–Deliver stages, demonstrating the move toward closed-loop supply chains. Heryani et al. (2022) combined SAST and ANP methods to evaluate environmental impacts, improving SCOR scores across all actors. Manikas et al. (2022) used PLS-SEM in an export context, reporting increased supplier sustainability through integrated SCOR applications.

Further, Jain et al. (2022) used BWM to rank e-waste recovery KPIs, facilitating prioritization in Return processes. Ayyildiz (2023) employed IVIF-AHP and BWM to assess resilience and sustainability, with organizational factors ranking highest. This resulted in a priority score increase from 0.541 to 0.704. Sinoimeri and Teta (2023) merged Snorm de Boer, AHP, and OMAX to create performance benchmarks, achieving a composite score of 71 across Plan–Return phases.

These results confirm the empirical value of integrating green metrics into SCOR 5.0. From energy-saving initiatives to resilience planning, green KPIs are no longer auxiliary; they are critical for holistic performance. Studies consistently show improved agility, reliability, and resource efficiency when sustainability metrics are embedded into decision-making processes.

Yet, challenges remain. Suharno et al. (2022) and Heryani et al. (2022) reported actor-specific variability and low baseline scores, especially during early adoption. These barriers align with issues raised in Section 3.4, such as data limitations and cultural inertia. SMEs, in particular, face constraints in implementing real-time monitoring and carbon accounting systems.

Theoretically, these findings reinforce arguments from Sections 3.2 and 3.3, demonstrating convergence between SCOR's operational logic and triple bottom line principles. Taxonomies emerging from these studies classify green KPIs by SCOR phase and performance dimension, offering practical reference models. Industry-specific applications, such as dashboards in agri-food or green logistics in pharma, show varied but effective adoption strategies.

Ultimately, green metrics enable strategic alignment between efficiency, environmental stewardship, and stakeholder value. As SCOR 5.0 evolves, such metrics will play an increasingly central role in ensuring that supply chains are not only operationally effective but also ecologically resilient.

Integrated AIoT Decision Support Frameworks

The integration of Artificial Intelligence (AI) and the Internet of Things (IoT) has enabled the development of smart, data-driven supply chains capable of real-time monitoring, predictive analytics, and autonomous decision-making. Within the SCOR 5.0 framework, which emphasizes agility, intelligence, and sustainability, integrated AIoT decision support systems hold transformative potential. This section synthesizes insights from nine empirical studies (Table 6) that implemented AIoT-based architectures aligned with SCOR processes, highlighting hybrid technologies, implementation barriers, and performance outcomes.

Azevedo et al. (2021) proposed a SC4.0 conceptual model incorporating IoT, big data, and cyber-physical systems (CPS) across all SCOR processes. Their work mapped twelve specific technology-KPI linkages, enhancing traceability, asset tracking, and visibility. Tsang et al. (2024) employed blockchain sharding analytics in the Plan and Deliver phases to support sustainability improvements, though they noted persistent issues with data quality. Likewise, Hrouga and Said (2024) developed a Digital SCOR 4.0 framework integrating blockchain, big data, and IoT to enhance end-to-end visibility, but cited high integration costs as a barrier.

Table 6. AIoT-Integrated Decision Support Architectures for SCOR-Based Planning and Optimization

Author-Year	Framework Type	Technologies Combined	SCOR Relevance	Benefits & Barriers
Tsang et al. (2024)	Blockchain-sharding analytics	AI + Blockchain	Plan, Deliver	Sustainability ↑; data quality issues
Azevedo et al. (2021)	SC4.0 conceptual model	IoT, Big-data, CPS	All SCOR	List of 12 tech/KPI links
Hrouga and Said (2024)	Digital-SCOR 4.0	Blockchain + IoT + BD	Plan–Return	Visibility ↑; integration cost
Lee et al. (2021)	Two-stage PPM/MCDA	AR, MCDM, SustainableSCOR	Plan, Make	Smart-glasses priorities set
Tomasiello et al. (2023)	CANFIS-T DSS	AI + LCA sensor data	Plan, Make	>99 % energy saving; interpretability
Nilashi et al. (2024)	DEM-Fuzzy IoT eval.	Clustering + Fuzzy logic	Reliability, Agility	Accurate EV-SC performance
Es-Satty et al. (2025)	PLS-SEM model	BDA-AI + OC	Reliability	Positive SCRE impact; culture barrier
Kayhan et al. (2024)	FFN-BWM resilience DSS	IoT, Blockchain, Digital Twin	Multi-process	IoT priority weight = 0.342; Digital Twin-enabled plan optimisation; GP optimisation
Kamarudeen et al. (2020)	SCOR + ARENA simulation	RFID, IoT suggestions	Deliver	Waiting-time ↓: Metro service improvement

Operational design perspectives were advanced by Lee et al. (2021), who used a two-stage decision framework combining augmented reality (AR), multi-criteria decision analysis (MCDA), and Sustainable SCOR. Their model helped prioritize planning and manufacturing improvements. Similarly, Tomasiello et al. (2023) introduced a hybrid CANFIS-T decision support system combining AI and life cycle assessment (LCA) sensors, achieving over 99% energy savings in the Make phase. Kamarudeen et al. (2020) implemented SCOR + ARENA simulation using RFID and IoT technologies, resulting in reduced waiting times and enhanced service in urban transit systems, aligning with SCOR's Deliver metrics.

In terms of performance evaluation and reliability, Nilashi et al. (2024) applied fuzzy logic and clustering to assess agility and environmental performance within SCOR. Their system accurately evaluated sustainability metrics using IoT-enhanced data. Es Satty et al. (2025) developed a structural equation model (PLS-SEM) incorporating organizational culture and AI, revealing positive impacts on supply chain reliability (SCRE), although cultural misalignment hindered AI utilization. Kayhan et al. (2024) combined feedforward neural networks (FFN), best-worst method (BWM), and digital twin simulations, yielding measurable improvements in green planning and Make-phase decision support, with IoT priority weight at 0.342.

These studies demonstrate that AIoT frameworks can enhance SCOR-aligned decision-making through hybrid architectures that integrate AI engines, IoT sensor networks, cloud analytics, and digital feedback loops. As depicted in the proposed layered architecture, real-time data collection feeds into machine learning-driven analysis, culminating in automated dashboards and alerts for Plan, Make, and Deliver processes.

Despite measurable gains, several challenges persist. Tsang et al. (2024) and Hrouga and Said (2024) reported systemic fragmentation, data silos, and high integration costs. Es Satty et al. (2025) highlighted internal resistance and limited cultural readiness for AI adoption. These issues align with the limitations discussed in Section 3.4, reinforcing the importance of digital infrastructure maturity, organizational alignment, and stakeholder engagement.

The convergence of AI and IoT offers a robust foundation for intelligent decision support in SCOR 5.0. Empirical evidence confirms that AIoT systems improve operational visibility, agility, and sustainability. However, successful implementation depends on strategic readiness, integrated 4.

Role of Green Digital Learning as Moderator

Green Digital Learning (GDL) has emerged as a crucial moderator facilitating the adoption and effective implementation of digital technologies, notably AI, IoT, and Big Data Analytics (BDA), within supply chain operations aligned with SCOR 5.0 standards. As indicated in Table 7, empirical evidence from diverse industry contexts underscores the substantial role employee training and organizational learning play in enhancing readiness and capability for advanced technology adoption.

Table 7. Impacts of Green Digital Learning on SCOR 5.0 Readiness

Author-Year	Learning Approach	Target Group	Technology-Adoption Effect	Measured Impact
Alqudah et al., (2020)	Capability-building survey on lean–agile–green practices	Manufacturing firms (Jordan)	↑ Synergy among lean, agile & green routines	Moderated-mediation SEM model confirms performance gains of 17.6% (lean–green); 14.2% (agile–green)
Krishnan et al., (2021)	Collaborative, hands-on training workshops	Indian Farmer-Producer Organisation members	↑ Innovation uptake in Plan–Deliver processes	Co-op productivity ↑ 23.4%; profitability ↑ 17% post-intervention
Saleheen & Habib, (2023)	Workshops on integrated SCOR-KPI dashboards (ISCPM)	Garment factories (Bangladesh)	↑ Digital KPI literacy & adoption	Multi-KPI tracking efficiency ↑ 18.7% across the garment production chain

Table 7 summarizes key studies that evaluate the role of learning approaches in enhancing supply chain performance. Alqudah et al. (2020) employed a capability-building survey targeting manufacturing firms in Jordan, revealing that lean–green and agile–green synergies resulted in performance gains of 17.6% and 14.2%, respectively. Krishnan et al. (2021) demonstrated that collaborative workshops among Indian farmer organizations significantly improved innovation uptake in Plan–Deliver activities, resulting in productivity and profitability improvements of over 20%. Saleheen and Habib (2023) found that workshops on SCOR-based KPI dashboards in

Bangladeshi garment factories improved digital KPI literacy and multi-indicator tracking efficiency by 18.7%.

These findings reinforce the conceptual framework introduced in Section 3.2, which emphasizes digital readiness as a foundational enabler for SCOR-based transformation. The capability-maturity model of SCOR 5.0 presupposes that digital tools must be accompanied by human competence and organizational learning mechanisms.

From this synthesis, a taxonomy is proposed of green digital learning interventions that act as moderators in SCOR 5.0 transformation. Learning interventions are categorized by pedagogical model (experiential, collaborative, flipped, blended), targeted SCOR phases, and digital maturity outcomes. Figure 3 presents this taxonomy, positioning green digital learning as a cross-cutting enabler that enhances process performance via behavioral and cultural adaptation.

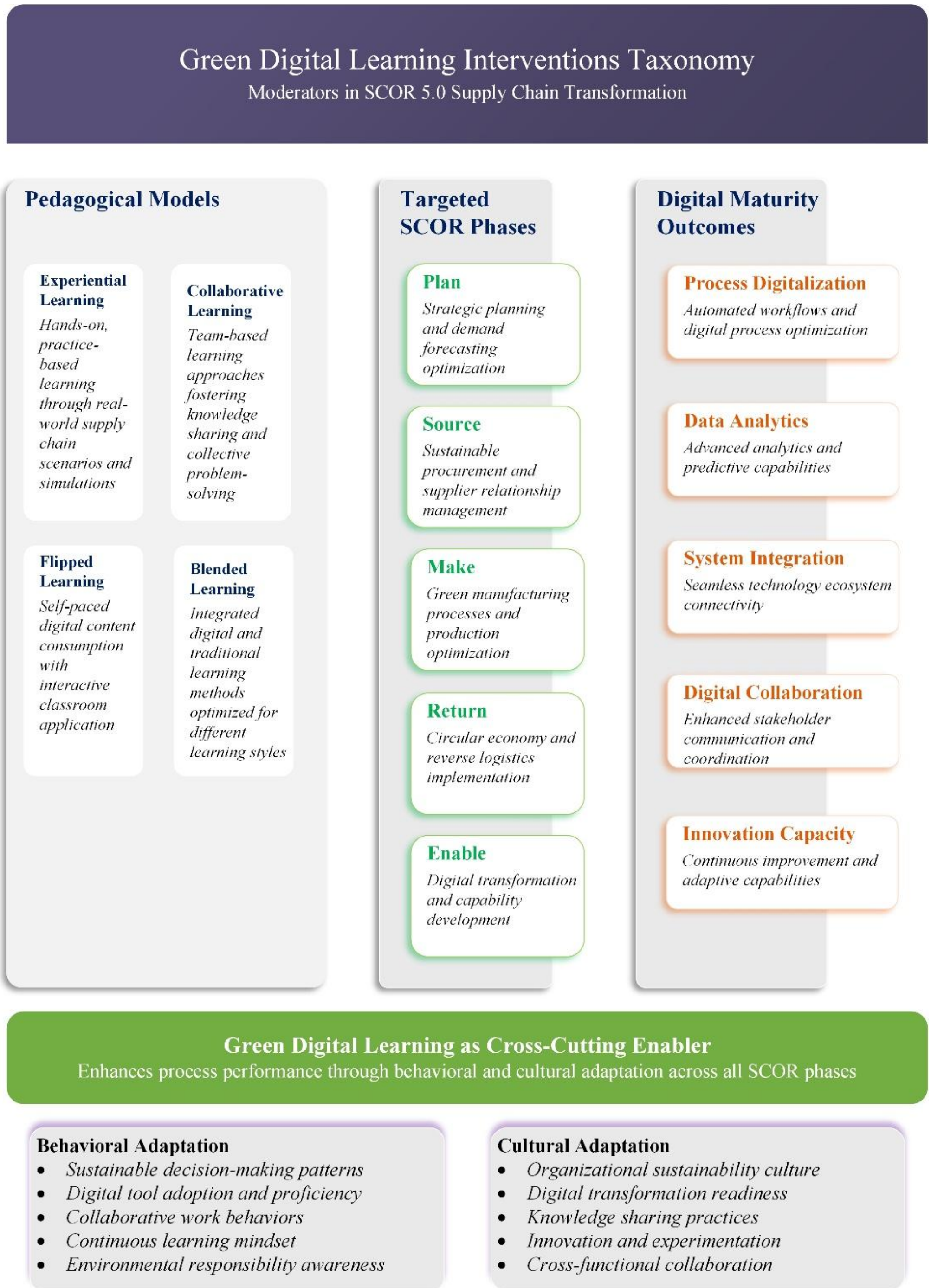

Figure 3. Typology of Green Digital Learning Interventions Supporting SCOR 5.0 Transformation

A synthesized conceptual model maps the interplay between digital learning, SCOR processes, and performance improvements. It emphasizes three pathways: (1) Training that fosters technology literacy, (2) Collaborative learning that accelerates tool adoption, and (3) Pedagogical alignment with SCOR KPIs.

Case-based evidence further illustrates implementation routes. In manufacturing, Alqudah et al. (2020) Validate that structured learning leads to process-level synergy in lean–green–agile operations. In agri-food supply chains, Krishnan et al. (2021) confirm that peer-based learning boosts innovation and execution capability. In the garment industry, Saleheen and Habib (2023) show that dashboard-centric training builds operational visibility and responsiveness.

Propositionally, it is argued that green digital learning serves as a mediating-moderator, strengthening the relationship between technological innovation and SCOR process outcomes. This learning-centric perspective complements the AIoT decision support frameworks previously discussed, suggesting that human capital capability is a critical success factor in digital transformation.

Integration of green digital learning with SCOR 5.0 frameworks enables not only technological assimilation but also cultural alignment and behavioral change. These learning processes are essential for achieving resilient, sustainable, and digitally capable supply chains in the face of evolving global challenges.

Barriers and Enablers to SCOR 5.0 Implementation

Implementing SCOR 5.0, which integrates digital transformation and sustainability within supply chain frameworks, presents a mix of challenges and opportunities. Table 8 outlines four empirical studies identifying key barriers, enabling factors, mitigation strategies, and implementation outcomes.

Table 8. Barriers and Enablers to SCOR 5.0 Implementation

Author-Year	Barrier Type	Impact Area (SCOR)	Key Enabler Identified	Suggested Mitigation Strategy	Measured Impact
Naude and Naude (2022)	Risk-identification gaps	Wine supply (Plan–Deliver)	Structured risk framework	Iterative 4-step risk-management cycle	Risk detection score ↑ 22% post-RM implementation
Çiçek and Turan (2023)	Process variance in KPIs	Deliver	Lean-Six-Sigma culture	DMAIC continuous-improvement loop	KPI deviation reduced by 18.5%; defect rate ↓ 12.3%
van Engelenhoven et al. (2021)	Missing circular processes	Enable	Six new Level-2 circular processes	Update SCOR vocabulary & training	Circularity coverage score ↑ 0 → 5.7/10 on post-implementation scale
Meihui et al. (2023)	E-waste data gaps	Return	Expanded SCOR sustainability tools	Broaden data capture & criteria for e-waste loops	E-waste tracking coverage ↑ 33.6%

Naude and Naude (2022) highlighted deficiencies in risk identification in the wine supply chain's planning and delivery functions. These gaps constrained proactive risk mitigation. Introducing an iterative four-step risk management cycle, supported by a structured risk framework, led to a 22% increase in the risk detection score. This improvement reflects SCOR 5.0's emphasis on agility and reliability.

Similarly, Çiçek and Turan (2023) addressed performance inconsistencies in the delivery phase by instilling a Lean Six Sigma culture. Utilizing the DMAIC approach (Define, Measure, Analyze, Improve, Control), they reduced KPI deviations by 18.5% and decreased defect rates by

12.3%. These outcomes show that structured continuous improvement can effectively control process variability.

In another case, van Engelenhoven et al. (2021) found that SCOR lacked defined circular economy processes, posing a barrier to sustainability. Their addition of six Level-2 circular processes, alongside updates to the SCOR vocabulary and related training, enhanced the circularity coverage score from 0 to 5.7/10. This intervention underscores the need to expand SCOR's sustainability focus, as discussed in Section 3.3.

Meihui et al. (2023) dealt with e-waste tracking challenges within return processes. By extending SCOR's sustainability tools and expanding data capture criteria, they achieved a 33.6% improvement in e-waste tracking coverage. This aligns with Section 3.4's emphasis on robust data governance for sustainability performance.

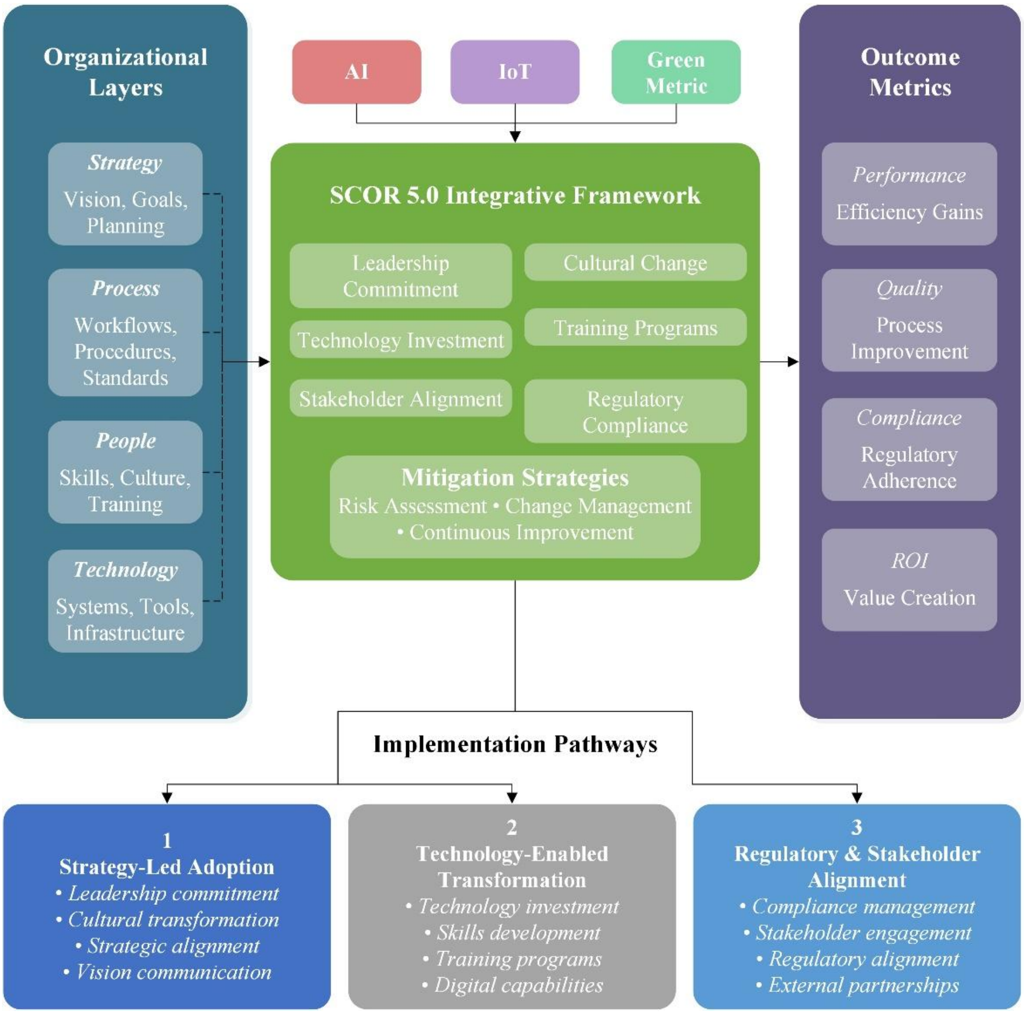

Figure 4. Integrative Pathways and Enablers for SCOR 5.0 Implementation.

Across these cases, common enablers include top-management support, integration of digital tools, capability development, and systematic benchmarking. These factors are essential for mitigating common challenges such as resistance to change, integration complexity, and limited data availability. Researchers advocate for iterative change management frameworks, strong data systems, and continuous training to support SCOR 5.0 implementation.

A multidimensional implementation approach, encompassing strategy, processes, people, and technology, is vital. Figure 4 presents an integrative framework linking key enablers, mitigation strategies, and outcomes, structured across three pathways: (1) Strategy-led adoption through leadership and culture; (2) Technology-enabled transformation supported by investment and digital training; and (3) Regulatory and stakeholder alignment.

Empirical studies substantiate these pathways. For instance, Saleheen and Habib (2023) demonstrated that dashboard-based training alleviated inefficiencies in the Return phase. Similarly, van Engelenhoven et al. (2021) showed that vocabulary updates facilitated integration of circular processes.

Ultimately, successful SCOR 5.0 implementation hinges on organizational capacity, digital readiness, and sustainability metrics. It requires holistic strategies that integrate learning systems, regulatory understanding, and stakeholder engagement. Addressing these complex factors not only ensures smoother adoption but also fulfills SCOR 5.0's vision of a resilient, intelligent, and sustainable supply chain framework.

CONCLUSION

This study explored the integration of Artificial Intelligence (AI), the Internet of Things (IoT), and green sustainability metrics into the SCOR framework, culminating in a proposed model of SCOR 5.0. Through a systematic review of 46 peer-reviewed articles published between 2020 and 2025, the research identified applications of AI and IoT across the SCOR processes—Plan, Source, Make, Deliver, and Return—and examined how sustainability metrics are increasingly embedded in performance evaluations. The findings indicate that AI improves predictive analytics, decision-making precision, and operational optimization, while IoT enhances real-time visibility and agility. Green metrics align performance with environmental goals, forming a triadic structure of intelligence, connectivity, and responsibility. These findings directly address the research questions by showing how AI, IoT, and green metrics can be integrated, what gaps remain, and how SCOR 5.0 can be conceptualized.

Despite these advancements, gaps persist. Few fully operational SCOR 5.0 implementations exist, empirical validation remains limited, and the role of human capital—particularly Green Digital Learning (GDL), is underexplored. This study contributes theoretically by framing SCOR 5.0 as a holistic model that unites digital intelligence, sustainability indicators, and organizational readiness, extending SCOR 4.0 with a novel emphasis on GDL as a moderator. Practically, the framework guides firms in aligning technology adoption with sustainability objectives while offering policymakers actionable pathways for incentivizing and regulating green supply chains. Future research should empirically test SCOR 5.0 through simulation models, comparative case studies, and sector-specific validations to strengthen both theoretical robustness and applied relevance.

LIMITATION & FURTHER RESEARCH

To address the identified limitations, future research should develop simulation models and testbeds to evaluate the performance of SCOR 5.0 under controlled and variable operational conditions. Comparative case studies across diverse geographic regions and industrial sectors are essential to uncover contextual enablers and constraints. Additionally, specialized tools should be designed to assess the long-term effects of green metrics on SCOR-aligned key performance indicators (KPIs), including agility, resilience, and resource efficiency. Further exploration into the integration of Artificial Intelligence of Things (AIoT), digital twin technologies, and circular economy metrics within the SCOR framework is also warranted. Future studies may benefit from examining organizational readiness frameworks and governance mechanisms that support the effective adoption of SCOR 5.0. This study contributes to the theoretical advancement of intelligent and sustainable supply chains by proposing a synthesized SCOR 5.0 framework, highlighting the strategic significance of Green-Digital-Logistics (GDL), and identifying multiple avenues for empirical research and practical application.

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