Physical AI as a Governance Layer in Sustainable Supply Chains: Rethinking Accountability and Operational Autonomy

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Abstract

This paper conceptualises physical AI as a distinct governance layer within sustainable supply chains. As AI becomes embedded in robotics, sensors, computer vision, and edge control systems, operational decisions regarding material flows are increasingly executed autonomously and in real time. The research question explores how this rise in operational autonomy reshapes accountability structures and sustainability governance in supply chains. The aim is to move beyond efficiency-focused digital transformation narratives and to analyse physical AI as an organisational and systemic governance mechanism. The study adopts a conceptual and theory-building approach, integrating insights from supply chain governance, sustainability management, and AI governance research. It develops a governance-layer framework that explains how increasing algorithmic autonomy alters decision visibility, responsibility allocation, and the measurement of environmental performance. Three structural tensions are identified: operational autonomy versus managerial accountability, data-driven optimisation versus environmental externalities, and network-level efficiency versus local sustainability impacts. The findings suggest that physical AI can strengthen resilience and resource coordination in sustainable supply chains, yet it simultaneously creates accountability gaps when sustainability criteria are not embedded within algorithmic architectures. The paper contributes by linking sustainable supply chain governance with AI governance and by clarifying how physical AI transforms managerial control. For organisations and policymakers, the results highlight the need to integrate sustainability metrics directly into autonomous decision systems. The study's conceptual nature is a limitation; further empirical research should test the governance-layer framework across industries.

Keywords: physical AI; governance layer; sustainable supply chains; operational autonomy; accountability; AI governance.

1 Introduction

Digital transformation in supply chains has evolved from information integration to cyber-physical execution. Early digitalisation focused on Enterprise Resource Planning (ERP) systems, visibility platforms, and predictive analytics. More recent advances integrate artificial intelligence with robotics, sensors, and edge systems, enabling real-time execution of operational decisions.

Jackson et al. (2024) conceptualise generative artificial intelligence (AI) in supply chain and operations management as a capability-based architecture encompassing perception, prediction, reasoning, learning, and adaptation. Their framework positions AI as an enabler across 13 decision domains, from demand forecasting to disruption management. However, the underlying logic remains primarily capability-driven rather than governance-driven.

Similarly, Groshev et al. (2021) demonstrate that digital twins integrated with AI agents enable cyber-physical systems to perform autonomous movement prediction and robotic control. Lazaroiu et al. (2024) extend this approach to cognitive digital twin-based Internet of Robotic Things (IoRT) systems operating within immersive industrial metaverses, where cooperative multi-agent AI orchestrates production and logistics in real time.

These developments collectively mark the rise of what can be termed physical AI: AI embedded in cyber-physical infrastructures that not only advises but also directly executes material coordination.

The shift from advisory AI to executive AI has significant governance implications. Traditional supply chain governance assumes that managerial actors oversee optimisation processes (Busse et al., 2017; Seuring & Müller, 2008). However, when routing algorithms dynamically reallocate freight, based on cost and speed, and robotic warehouses autonomously prioritise fulfilment, decision-making authority becomes structurally embedded in code.

The central problem addressed here is therefore not technological efficiency but governance redesign. Physical AI introduces operational autonomy without a corresponding transformation in accountability mechanisms. The governance question shifts from “Who decides?” to “Who designed the decision architecture?”

2 Theoretical Foundations

2.1 Physical AI and Cyber-Physical Execution

Ivanov & Dolgui (2021) demonstrate that digital twins enhance supply chain resilience through real-time disruption modelling. However, their framework still relies on managerial interpretation of model outputs. In contrast, Groshev et al. (2021) describe AI-enabled digital twins that autonomously close decision loops at edge or fog computing levels, effectively decentralising operational authority.

Jackson et al. (2024) emphasise AI’s capacity to enhance risk management, inventory control, and network design. Their capability-based perspective, grounded in the resource-based view, highlights strategic potential but does not explicitly address governance allocation.

Lazaroiu et al. (2024) advance the field by describing cooperative AI agents operating in robotic manufacturing systems across the IoRT and 5G infrastructures. In this context, AI acts as an orchestrator of physical flows. Control shifts from being episodic to continuous.

Wang et al. (2021) describe the shift towards smart and intelligent manufacturing ecosystems, where cyber-physical integration, pervasive sensing, and data-driven control increasingly enable near-real-time coordination across production and logistics interfaces. In supply networks, this shift is evident in the growing use of algorithmic routing and dispatch decisions, which dynamically reallocate transport flows in response to congestion, cost, and demand conditions, thus moving from decision support to decision execution (Marufuzzaman & Ekşioğlu, 2017).

These studies collectively indicate that AI has crossed a structural boundary, moving from analytical augmentation to operational execution. Once embedded in cyber-physical loops, AI decisions become materially consequential and temporally irreversible.

2.2 Organisational AI Governance

Mäntymäki et al. (2022) define organisational AI governance as the system of structures and processes that ensure AI use aligns with strategic, legal, and ethical requirements. Their framework positions AI governance alongside corporate and IT governance, emphasising the formal allocation of accountability.

Camilleri (2024) links AI governance to corporate social responsibility and ESG, arguing that fairness, transparency, privacy, and accountability must be embedded in AI design and deployment.

Kuziemski & Misuraca (2020) introduce the "tragic double bind" of governing algorithms while also governing with algorithms. They emphasise that optimisation criteria are inherently political and value-laden. Their question – "for what are we optimising?" – is directly applicable to AI-enabled supply chains.

Janssen (2025) conceptualises generative AI as a complex, adaptive socio-technical system. In this view, governance extends beyond control to include direction and stewardship. Responsibility is distributed among vendors, providers, and users.

Recent work on human–artificial intellectual capital further emphasises that governance challenges arise not only from technological capabilities but also from the interaction between human and artificial knowledge resources (Caputo, 2024).

Collectively, these studies suggest that AI governance must be systemic, multi-actor, and outward-looking. However, none explicitly address AI embedded in inter-organisational logistics networks.

2.3 Sustainable and Resilient Supply Chain Governance

Negri et al. (2021) demonstrate ongoing conceptual confusion between sustainability and resilience. Sustainability emphasises efficiency and long-term environmental performance, whereas resilience focuses on adaptive effectiveness during disruption. AI optimisation may prioritise one over the other depending on the objective functions.

Zavala-Alcívar et al. (2020) propose an integrated resilience–sustainability framework and emphasise governance mechanisms to reduce vulnerability and enable strategic adaptation.

Wang et al. (2020) present a rigorous Multi-Regional Input-Output/Data Envelopment Analysis (MRIO-DEA) methodology for measuring environmental performance in global supply chains. Their empirical findings indicate significant environmental inefficiencies that could be reduced through improved configuration.

These studies show that sustainability governance requires performance measurement, coordination, and strategic capability. However, they assume management mediated by humans.

2.4 Algorithmic Optimisation and Governance Levers

Multi-objective optimisation research makes governance choices explicit. Khalili-Fard et al. (2024) developed a model for closed-loop supply chains that balances costs, emissions, and job creation to achieve the SDGs. Isaloo & Paydar (2020) show how objective weights affect trade-offs between cost and environmental performance. Ala et al. (2024) generate Pareto frontiers for economic, environmental, and social goals in healthcare supply chains.

These models show that optimisation parameters encode value choices. Objective weights, constraints, and risk tolerances serve as governance levers. When embedded in physical AI systems, these levers become algorithmic determinants of environmental outcomes. Thus, governance in AI-enabled supply chains shifts from ex post monitoring to ex ante parameter design.

The following evidence-mapping table synthesises the key literature clusters. It highlights how research on cyber-physical AI systems, organisational AI governance, sustainable and resilient supply chains, and multi-objective optimisation each address elements of control and performance; however, none explicitly conceptualise physical AI as a governance layer within sustainable supply chains.

Table 1: Evidence Mapping of Literature on Physical AI, AI Governance and Sustainable Supply Chains

Literature Stream	Representative Studies	Core Theoretical Contribution	Governance Implication	Identified Integrative Gap
AI and Cyber-Physical Execution in Supply Chains	Jackson et al. (2024); Groshev et al. (2021); Lăzăroiu et al. (2024)	AI/digital-twin/IoRT architectures enabling real-time execution	Operational autonomy; locus of control shifts (edge–cloud)	Accountability allocation under closed-loop execution remains implicit
Organisational and Responsible AI Governance	Mäntymäki et al. (2022); Camilleri (2024); Janssen (2025)	AI governance definitions and CSR-oriented frameworks; Complex Adaptive System (CAS) view	Accountability, transparency, joint responsibility; outward orientation	Limited application to inter-organisational, physically executed supply chains
Public and Algorithmic Governance Tensions	Kuziemski & Misuraca (2020)	"Governing with/while governing algorithms"; optimisation	Value-laden objective setting; opacity and power asymmetries	Not operationalised for supply-chain sustainability governance
Sustainable and Resilient Supply Chain Governance	Negri et al. (2021); Zavala-Alcívar et al. (2020); Wang et al. (2020)	Integrated sustainability–resilience concepts; performance measurement	Metrics, coordination, resilience governance; efficiency trade-offs	Human-centred oversight assumed; autonomy not theorised
Multi-objective Optimisation and Trade-offs	Khalili-Fard et al. (2024); Isaloo & Paydar (2020); Ala et al. (2023)	Formal trade-offs via objectives/constraints; Pareto-front logic	Parameters act as governance levers shaping outcomes	Weak linkage to real-time autonomous systems and accountability

Source: own.

Table 1 shows that, although each literature cluster addresses aspects of control, coordination, performance measurement, or responsibility, these insights remain largely isolated. Cyber-physical and digital-twin research emphasises operational autonomy but rarely clarifies how accountability is assigned when decision loops are closed algorithmically. AI governance work develops principles and mechanisms for responsible use but typically abstracts from inter-organisational, materially consequential logistics execution. Sustainable and resilient supply chain scholarship provides governance and measurement foundations yet implicitly assumes human-centred oversight. Multi-objective optimisation studies make trade-offs explicit through weights and constraints, without theorising how such parameter choices become embedded governance levers in real-time autonomous systems. The lack of an integrative framework that explicitly conceptualises physical AI as a governance layer– linking autonomy, embedded sustainability criteria, and accountability transparency– motivates the present study.

3 Research Question and Purpose

Research Question: How does physical AI, conceptualised as a governance layer in sustainable supply chains, reshape accountability structures, optimisation logic, and sustainability performance management under increasing operational autonomy?

Purpose: To develop a governance-layer framework that integrates AI governance, cyber-physical systems, and sustainable supply chain governance, and to clarify how algorithmic autonomy transforms the allocation of accountability.

4 Method

This study adopts a conceptual theory-building methodology, following Jaakkola's (2020) framework for designing conceptual articles. Instead of testing predefined hypotheses, the paper develops an integrative theoretical model through structured synthesis and model development. The methodological approach proceeds in three stages.

First, a focused evidence-mapping review was conducted using high-quality peer-reviewed research identified through the Consensus-assisted search process. The selected studies were grouped into four thematic streams: cyber-physical AI execution systems, organisational AI governance, sustainable and resilient supply chain governance, and multi-objective optimisation research. The aim of this stage was not exhaustive coverage but theoretical saturation within each stream.

Second, a cross-stream comparison was conducted to identify structural asymmetries. In particular, the analysis examined whether operational autonomy in cyber-physical systems is matched by corresponding governance mechanisms in sustainability research. This comparative step revealed a persistent disconnect: AI execution literature emphasises capability and responsiveness; governance literature emphasises accountability and ethics; sustainability research emphasises performance measurement and coordination; optimisation models formalise trade-offs but rarely frame them as governance decisions.

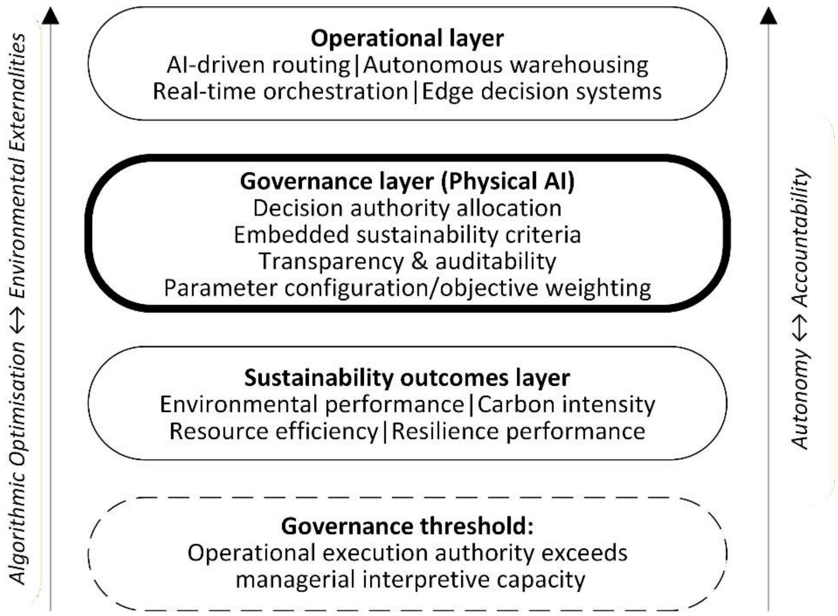
Third, these insights were synthesised into a governance-layer model that conceptualises physical AI as a structural mediator between operational systems and sustainability outcomes. The model introduces the notion of a governance threshold, representing the point at which algorithmic execution authority exceeds managerial interpretive capacity. The resulting framework is explanatory rather than predictive and aims to clarify conceptual relationships rather than produce empirical generalisations.

5 Results: The Governance-Layer Framework

5.1 Physical AI as a Governance Layer

Figure 1 presents physical AI not as a technological enhancement, but as a governance layer embedded between operational processes and sustainability outcomes. In traditional supply chain governance models, operational decisions are subject to managerial review, policy oversight, and performance monitoring. Physical AI restructures this architecture by embedding optimisation logic directly into cyber-physical execution loops.

Figure 1 Governance-Layer Model of Physical AI in Sustainable Supply Chains



Source: own.

In cyber-physical systems described by Groshev et al. (2021) and Lazaroiu et al. (2024), AI agents operate at edge and fog levels, autonomously closing control loops. In these systems, routing, dispatching, and scheduling decisions are executed continuously without episodic human validation. Decision authority becomes algorithmic.

The governance-layer concept captures this structural relocation of authority. It emphasises that governance is not limited to oversight mechanisms or compliance audits. Instead, governance is embedded in algorithmic design parameters, objective functions, and optimisation constraints. When cost, time, and service-level indicators are prioritised in objective functions, these priorities become institutionalised as operational realities.

Multi-objective optimisation research makes this dynamic explicit. Khalili-Fard et al. (2024), Isaloo & Paydar (2020), and Ala et al. (2024) show that economic, environmental, and social goals can be weighted differently within algorithmic models. The selection of weights, constraints, and acceptable risk levels determines which Pareto-optimal solution is implemented. In AI-enabled supply chains, these parameter choices are no longer static planning decisions; they are embedded in systems that operate continuously and adaptively.

Thus, physical AI serves as a governance layer by operationalising value choices in code. It allocates decision-making authority, defines optimisation criteria, and shapes the visibility of trade-offs.

5.2 Governance Threshold and Stages of Autonomy

The governance threshold concept formalises the point at which operational autonomy exceeds managerial oversight. This threshold is reached when algorithmic systems make real-time execution decisions more quickly and frequently than managers can meaningfully interpret or intervene. It is therefore not a sudden technological event, but a gradual transition across stages of AI-enabled decision-making.

In the first stage, assisted decision-making, AI systems support managers by generating recommendations, forecasts, or alternative courses of action. Decision authority remains with human operators, who evaluate and approve proposed actions. Accountability structures are therefore largely unchanged, as managerial judgement remains the final decision point.

In the second stage, delegated execution, bounded operational tasks are assigned to AI systems. Algorithms may carry out predefined routing, scheduling, or inventory decisions within established parameters, while human actors retain supervisory authority and can intervene when necessary. Responsibility becomes more distributed, but decision visibility remains sufficiently high for meaningful oversight.

In the third stage, autonomous orchestration, AI systems continuously coordinate and reconfigure operational processes across interconnected cyber-physical environments. Decisions are executed in real time and at a scale that exceeds human monitoring capacity. Human intervention becomes exceptional rather than routine, and accountability increasingly shifts from operational managers to system designers, developers, and those responsible for configuring optimisation parameters.

The governance threshold lies between delegated execution and autonomous orchestration. Kuziemski & Misuraca (2020) argue that governing algorithms while simultaneously governing with algorithms creates structural opacity. Janssen (2025) extends this reasoning by describing AI as a complex adaptive socio-technical system in which responsibility is distributed among vendors, operators, and users. When such systems autonomously execute supply chain decisions, tracing accountability becomes increasingly difficult.

The threshold does not imply a dramatic loss of control; rather, it marks a qualitative shift in where control resides. Control shifts from operational actors to architectural designers and parameter setters. Sustainability governance thus becomes a matter of design rather than supervision. Beyond this threshold, accountability, sustainability criteria, and acceptable trade-offs must be embedded directly into the architecture of autonomous decision systems.

5.3 Structural Tensions

Three structural tensions become apparent when physical AI is conceptualised as a governance layer. The first tension concerns operational autonomy and accountability. As AI systems assume execution authority, responsibility becomes diffused. Organisational AI governance literature emphasises formal accountability structures (Mäntymäki et al., 2022) and ethical oversight (Camilleri, 2024). However, in inter-organisational supply chains, responsibility may be shared among AI vendors, logistics providers, and focal firms, creating ambiguity in environmental accountability.

The second tension concerns optimisation and environmental externalities. Sustainable supply chain research highlights performance measurement and environmental inefficiencies (Wang et al., 2020). However, optimisation models often prioritise measurable economic objectives unless environmental criteria are explicitly included. Without this inclusion, algorithmic efficiency may conflict with long-term ecological goals.

The third tension concerns resilience and sustainability. Negri et al. (2021) distinguish efficiency-oriented sustainability from effectiveness-oriented resilience. AI systems that enhance responsiveness and redundancy may increase energy consumption or carbon intensity if speed is prioritised over environmental optimisation. Physical AI thus introduces a structural balance between adaptive performance and ecological responsibility.

These tensions are not temporary implementation challenges but structural consequences of increasing algorithmic autonomy. As physical AI systems become more adaptive and interconnected, tensions between optimisation, accountability, resilience, and sustainability are likely to intensify rather than disappear. The governance challenge is therefore not whether to automate, but how to embed societal and environmental objectives into autonomous decision architectures.

6 Organisational Implications

The governance-layer perspective suggests that organisations must reconceptualise sustainability governance as an architectural function. Sustainability metrics should not remain external reporting tools appended to operational systems; instead, they must be integrated directly into optimisation logic and decision algorithms.

In practice, this means incorporating carbon-intensity measures, energy-consumption thresholds, and social-impact indicators into objective functions. It also requires formally assigning responsibility for parameter selection and algorithmic configuration. Governance becomes a matter of defining acceptable trade-offs in advance rather than auditing outcomes afterwards.

Furthermore, auditability must be redefined. Traditional audits assess documented decisions, whereas in autonomous systems, decisions are continuous and distributed. Organisations therefore require explainability mechanisms and traceability infrastructures capable of reconstructing algorithmic decision paths.

Governance redesign should precede large-scale automation. Otherwise, operational autonomy risks creating sustainability blind spots embedded in the system architecture.

7 Societal Implications

At the societal level, autonomous supply chains influence environmental footprints, regional labour markets, and global trade flows. When optimisation criteria are narrowly defined, environmental externalities may intensify without transparent deliberation.

Camilleri (2024) emphasises that AI governance must align with corporate social responsibility and ESG objectives. Janssen (2025) argues for an outward-looking governance perspective that prioritises societal concerns. Applied to supply chains, this implies that optimisation criteria should reflect broader sustainability commitments rather than only shareholder value.

Physical AI systems that coordinate transport flows and production schedules directly influence energy consumption patterns and emissions trajectories. Consequently, governance of these systems becomes a matter of public interest. Regulatory frameworks must therefore move beyond abstract AI ethics and address the material consequences of AI-enabled logistics execution.

8 Originality

The originality of this study lies in reframing physical AI from a capability enhancement to a governance architecture. Existing research treats AI as a tool for resilience, optimisation, or digital transformation. In contrast, this paper conceptualises AI as a structural layer that redistributes authority and encodes normative trade-offs.

Second, the paper integrates literatures that rarely intersect. Cyber-physical AI research focuses on technological integration; AI governance literature addresses ethical and organisational oversight; sustainable supply chain research examines performance measurement and coordination; optimisation models formalise trade-offs. The governance-layer framework synthesises these streams into a unified analytical model.

Third, the governance-threshold concept introduces a theoretical mechanism that explains when autonomy surpasses accountability. This mechanism clarifies why sustainability governance must shift from oversight to design stewardship.

9 Limitations and Further Research

The study is conceptual and therefore does not provide empirical validation. The governance-layer framework should be tested through case studies of AI-enabled logistics hubs, digital twin deployments, and autonomous routing systems. Future research could examine how carbon metrics are operationalised in real-time routing algorithms and how objective weights change over time in adaptive systems.

Quantitative modelling approaches, such as MRIO-based sustainability assessment (Wang et al., 2020), could be combined with AI optimisation outputs to measure the alignment between algorithmic decisions and environmental performance. Comparative studies across industries would further clarify how governance architectures differ under varying regulatory pressures.

10 Summary

Physical AI transforms sustainable supply chains by embedding decision-making authority within continuously operating, adaptive cyber-physical systems. This transformation introduces a governance layer that reallocates authority, encodes value choices, and reshapes accountability structures.

When algorithmic optimisation operates without embedded sustainability criteria, operational autonomy risks creating accountability gaps and environmental misalignment. The governance threshold marks the structural point at which managerial oversight no longer matches algorithmic execution authority.

Sustainable supply chain governance must therefore shift from supervisory control to architectural stewardship. Responsibility by design, rather than responsibility after the fact, becomes the defining principle of governance in AI-enabled supply networks.

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