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MANAGEMENT IN LOGISTICS: INTEGRATION OF ARTIFICIAL INTELLIGENCE AND TECHNICAL COMMUNICATION

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Abstract: This paper analyzes the integration of artificial intelligence (AI) and technical communication in contemporary logistics management, based on the premise that successful AI implementation extends beyond the technological dimension and requires systemic organizational and communicational integration. Drawing on recent literature in logistics, supply chain management, and technical/professional communication, the study identifies key factors for managing AI implementation: strategic positioning and use-case selection, data governance and system interoperability, model lifecycle management (MLOps), digital twins as an integration infrastructure, as well as explainability (XAI) and risk management. Special attention is given to the role of technical communication in data standardization, documentation of AI systems, ensuring transparency and institutional trust, and facilitating interorganizational coordination within supply networks. The findings indicate that technical communication functions as both an integrative and control mechanism, enabling operational reliability, scalability, and sustainability of AI solutions in logistics systems. It is concluded that the synergy between AI technologies and structured communication protocols forms the foundation of modern, transparent, and manageable logistics management in a digital environment.

Keywords: artificial intelligence; logistics management; technical communication; digital twins; explainable AI.

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Introduction

Contemporary logistics management is increasingly based on the ability of organizations to orchestrate flows of materials, information, and finances across networks of heterogeneous actors (suppliers, 3PL/4PL providers, carriers, customs authorities, distributors, and customers) under conditions of high uncertainty and pressure on costs, service levels, and sustainability. In this context, the integration of artificial intelligence (AI) is moving from the phase of experimentation to becoming a strategic management infrastructure: AI is used for demand forecasting, route and capacity optimization, inventory management, warehouse automation, and real-time decision-making (Franjić, 2022; Chen et al., 2024). However, as logistics decisions increasingly rely on data-intensive and often "black-box" models, technical communication comes to the forefront as a prerequisite for operational reliability, regulatory compliance, and organizational legitimacy of AI solutions—from the quality of specifications, data exchange standards, and documentation, to the explainability and ethical framing of decisions generated by models (Lunić & Ćesarević, 2025).

AI transforms logistics management primarily through its ability to integrate large volumes of data (IoT, telematics, WMS/TMS/ERP systems, and market signals) and convert them into recommendations or automated decisions. The work of Chen et al. systematizes dominant AI approaches in logistics optimization (e.g., machine learning, generative models, metaheuristics, and hybrid approaches) and emphasizes that performance is increasingly evaluated through sustainability criteria (emissions, waste, energy efficiency), thereby introducing multi-criteria trade-offs as a standard in management (Chen et al., 2024). At the same time, the emergence of generative AI (e.g., large language models) further expands the scope of application—from accelerating analytics and report generation to supporting decision-making and knowledge management—but also raises issues of reliability, integrity, and accountability in logistics and academic practices (Richey Jr. et al., 2023).

However, logistics is not only a problem of optimization; it is also a problem of coordination (Dašić et al., 2024; Kostadinović & Ilievska Kostadinović, 2025). In this context, digital twins become a key link in integrating AI with operations management. Digital twins in logistics enable multiple types of services (e.g., monitoring, prediction, optimization, control, and system integration) and identify core capabilities required to deliver these services—among which interoperability and data integration are central. This directly implies that the value of AI in logistics depends on the quality of technical communication: without precise semantic definitions of data, agreed protocols, clear interfaces, and documented model assumptions, a digital twin cannot reliably connect the physical and digital worlds nor support auditable and reproducible managerial decisions.

As AI models are increasingly embedded in decision-making processes, the need for explainability (XAI) and risk communication grows. In logistics management structures, where decisions affect costs, supply continuity, and safety, a “correct result” is not sufficient if it cannot be explained—why the decision was proposed, under which conditions it holds, and what its limitations are. Olan et al. analyze the role of XAI in decision support systems in supply chains and emphasize that XAI techniques (e.g., SHAP) contribute to the transparency of predictions and strengthen trust in decisions under uncertainty. From a logistics management perspective, this means that the “model” must also be viewed as a communication artifact: explanations (feature importance, scenarios, limitations) must be translated into the language of operational roles (planner, dispatcher, procurement, risk management) and embedded into procedures, SLA metrics, and escalation protocols (Olan et al., 2024).

At this point, the connection between AI and technical communication becomes explicit: implementing AI in logistics requires disciplined communication between data science teams, IT architecture, and operations, as well as with external partners and regulators. Technical communication here includes: (1) specifications and standards (data definitions, API agreements, quality metrics), (2) model documentation (purpose, scope of application, performance, biases, update procedures), (3) explainable user experiences (dashboards, alerting, rationale), and (4) ethical and governance guidelines (accountability, transparency, use of generative AI). In this regard, Ranade and Saravia provide a relevant contribution through a systematic review of AI ethics in technical and professional communication, emphasizing that communicators’ competencies must include understanding and evaluating AI technologies through ethical perspectives and practices that prepare organizations for responsible AI use (Mlađenović, 2025). Although their focus is not logistics as an industry, the implication is direct: logistics organizations cannot “manage” AI without managing communication about AI—especially when AI affects work practices, distribution of responsibilities, and decision-making with consequences for multiple stakeholders.

Therefore, the topic “Management in Logistics: Integration of Artificial Intelligence and Technical Communication” can be grounded in the view that AI is not merely a technological upgrade of logistics, but a transformation of managerial logic—from managing processes to managing socio-technical systems in which data, models, and communication protocols are as critical as vehicles, warehouses, and labor. Contemporary literature simultaneously highlights the breadth of AI applications (optimization and sustainability), the strategic importance of generative AI, the growing role of digital twins as an integration framework, and the need for XAI to ensure trust and auditability (Chen et al., 2024; Richey Jr. et al., 2023). At the same time, research in technical and professional communication indicates that the responsible and effective use of AI depends on communication competencies, ethical frameworks, and practices of documentation and explanation (Ranade & Saravia, 2024). Hence, the integration of AI and technical communication in logistics management represents a relevant and emerging research field that connects performance (efficiency and sustainability), risk management (transparency and explainability), and organizational capability (coordination and standardization) within a unified framework of modern logistics.

Literature Review

Recent literature increasingly shifts the focus from general claims about “transformation” toward empirically verifiable effects of AI in supply chain management and logistics networks. A systematic review by Culot, Podrecca, and Nassimbeni, based exclusively on empirical studies, shows that research findings cluster around four critical areas: data and system requirements, technology implementation processes, (inter)organizational integration, and performance, with a strong emphasis on contextual factors that shape outcomes (e.g., IT/analytics maturity and partner coordination) (Culot et al., 2024). This finding is important for logistics management because it implies that the success of AI solutions is not determined solely by the algorithm, but by the quality of integration into processes, roles, responsibilities, and decision-making protocols—which in practice is inseparable from technical communication (data specifications, process documentation, information exchange standards).

In the past two years, a distinct research stream has emerged focusing on generative AI (GenAI) and large language models in operations and supply chains. An empirical study by Li, Liu, Jin, Cheng, and Zhang shows that the “depth of use” of generative AI can contribute to SCM performance, with coordination (with suppliers and customers) acting as the key mechanism, while environmental dynamism moderates the strength of these relationships (Li et al., 2024). Complementarily, Jackson, Ivanov, Dolgui, and Namdar propose a capability-based framework that maps how AI/GenAI capabilities (learning, perception, prediction, interaction, adaptation, reasoning) can impact multiple decision-making domains in supply chain and operations management, thereby opening a research agenda for implementation and governance (Jackson et al., 2024). For the topic of integrating AI and technical communication, these studies are crucial because “coordination” is not only an organizational phenomenon but also a communicative one: it requires aligned data definitions, interoperable information flows, and explainable model recommendations that can be reliably interpreted across functions.

As AI increasingly assumes roles in prediction and recommendation (e.g., planning, resource allocation, risk management), the need for explainability grows—not only for “transparency” but also for operational usability and risk management. Kosasih et al., in their review of neurosymbolic XAI approaches in SCM, systematize the literature and highlight that explainability becomes a key junction between models and managerial decisions, particularly in complex and dynamic environments (Kosasih et al., 2024). At the empirical level, Sadeghi et al. show that XAI can enhance transparency and agile decision-making, which in turn strengthens cyber-resilience in supply chains (Sadeghi et al., 2024). From a technical communication perspective, these insights imply the need for standardized “explanation packages” (rationale, limitations, conditions of use, data quality) embedded in DSS tools, reports, and procedures—since trust and effectiveness of XAI are achieved only when explanations are communication-tailored to user roles.

Digital twins are increasingly positioned in recent studies as an integration layer that connects real-time data, models, simulations, and operational decisions. Zaidi, Khan, and Chaabane emphasize in their systematic review that digital twins for SCM must encompass both internal and external connections (suppliers–distributors, procurement–production–logistics) and rely on real-time synchronization and data-driven modeling to respond to disruptions (Zaidi et al., 2024). Guo and Mantravadi further link digital twins to the lean supply chain perspective and, through a systematic literature review, identify where digital twins have the greatest impact on processes and performance, as well as where gaps remain (e.g., “source” and “return”) (Guo & Mantravadi, 2025). In both cases, technical communication is a structural prerequisite: without clear specifications of digital representations, data semantics, API agreements, and transparent model versioning rules, digital twin initiatives remain “pilots” without scalability and manageability.

In parallel with SCM/logistics literature, technical and professional communication (TPC) studies analyze in detail how GenAI is transforming the practice of technical documentation and instructions—directly relevant to logistics (SOPs, manuals, incident response, training, SLAs). Reeves and Sylvia, in their review of research from 2023–2024, find that GenAI can be useful in certain aspects of work, but that risks and limitations must be systematically addressed through research, pedagogy, and practice (Reeves & Sylvia, 2024). An empirically oriented contribution is provided by Johnson-Eilola, Selber, and York, who show that AI-generated instructions may follow some documentation conventions, but that human-authored instructions are often superior for “consistent” tasks—an insight with direct implications for logistics procedures where errors have operational and safety consequences (Johnson-Eilola et al., 2024). Carradini further frames the “current moment” in TPC as a period in which AI tools are reshaping pedagogy, practice, and research, implicitly highlighting the need for organizations to prepare through standards, guidelines, and responsible management of tools and content (Carradini, 2024).

In the context of operationalizing AI in logistics, particular attention is given to real-time decision-making under conditions of uncertainty and disruption. Ivanov develops the concept of “digital supply chain management” based on a combination of simulation, analytics, and autonomous decision-making, in which AI plays a key role in predictive and prescriptive planning (Ivanov, 2021). This approach highlights the need for integrating diverse data sources and models into a unified decision-making system, while also pointing to limitations in terms of system robustness and adaptability in dynamic environments. For logistics management, this implies that AI implementation requires not only technical infrastructure but also clearly defined protocols for interpreting and escalating decisions.

Furthermore, Ivanov emphasizes that supply chain resilience increasingly depends on organizations' ability to use AI for simulating disruption scenarios and rapidly reconfiguring operations (Ivanov, 2021). In this context, technical communication acquires an additional dimension: it is not limited to documenting existing processes but extends to the structured representation of scenarios, model assumptions, and possible outcomes, enabling different actors to effectively participate in decision-making. In this way, AI systems evolve from "black boxes" into tools that support collaborative and transparent management of logistics networks.

One significant but often underdeveloped dimension in the literature on AI in logistics is data governance as a prerequisite for effective implementation. While many studies implicitly assume the availability of high-quality data, research shows that issues related to data quality, ownership, and accessibility represent major constraints on AI adoption in supply chains. Kache and Seuring emphasize that successful AI implementation depends on organizations' ability to establish robust data governance mechanisms, including standardization, integration, and quality control across the entire supply chain (Kache & Seuring, 2017). This aspect is particularly critical in logistics, where data originate from multiple systems and organizations, further complicating their alignment and reliability.

At the same time, the ethical and regulatory dimension of AI application is gaining increasing importance, with direct implications for accountability and decision-making in logistics systems. Floridi et al. emphasize that AI implementation must be guided by principles of transparency, accountability, and fairness in order to mitigate risks related to bias, opacity, and potential misuse (Floridi et al., 2018). In the logistics context, this means that organizations must develop not only technical but also managerial and communication mechanisms to ensure control and auditability of AI systems. This further confirms that technical communication plays a key role in operationalizing ethical principles through documentation, model explanations, and the definition of responsibilities in decision-making processes.

Synthesizing these insights, the literature indicates a clear line of connection: (i) AI and digital twins in logistics increase dependence on data quality, integration, and explainability; (ii) GenAI opens new opportunities but also increases the risk of incorrect or inadequate instructions and explanations; and (iii) technical communication (specifications, documentation, explanation, standardization) acts as the “glue” that enables AI solutions to become operationally reliable and managerially manageable in real-world logistics systems.

Managing the Implementation of Artificial Intelligence in Logistics Systems

Managing the implementation of artificial intelligence (AI) in logistics systems represents a managerial challenge of socio-technical integration: the goal is not merely the “introduction of an algorithm,” but the stable embedding of models into planning and execution processes, information systems (ERP/WMS/TMS), partner interfaces, and risk control regimes. Contemporary literature emphasizes that the effects of AI in logistics are conditioned by organizational and interorganizational factors at least as much as by technological performance (Culot et al., 2024).

The starting point of managing AI implementation is the strategic articulation of value (value proposition): whether the primary objective is cost efficiency, service level (OTIF), agility/resilience, sustainability (emissions, energy), or a combination of these. In logistics, AI is most commonly mapped to three classes of use cases: (1) predictive decisions (demand forecasting, ETA, risk), (2) prescriptive decisions (route optimization, capacity allocation, inventory), and (3) execution automation (warehouse automation, autonomous vehicles/robots, intelligent scheduling). The review by Chen et al. shows that contemporary trends are increasingly linked to sustainability criteria in optimization, which changes the objective function and introduces multi-criteria trade-offs as a standard of logistics management (Chen et al., 2024).

It is important to avoid “AI hype” and begin with a use-case portfolio that includes clear metrics and operational ownership (process owner). The empirically oriented SLR study by Culot et al. emphasizes that implementation outcomes cluster around data/system requirements, implementation processes, (inter)organizational integration, and performance—implying that use cases must not be defined solely technically, but also organizationally (Culot et al., 2024).

AI in logistics is “data-hungry”: model quality and decision stability depend on reliable, complete, and semantically aligned data. Managing implementation therefore requires formalized data governance (data ownership, quality rules, lineage, access, security) and a plan for integration with ERP/WMS/TMS systems and external sources (telematics, IoT, partners). In practice, the integration layer (ETL/ELT, APIs, event-driven processing) often becomes a critical success factor, because without it the model remains an isolated “pilot.”

The literature emphasizes that the technological effects of AI materialize only when data and systems are integrated into end-to-end decision-making and coordination flows (Richey et al., 2023; Culot et al., 2024).

The managerial framework must encompass the entire model lifecycle: from architecture selection and training, through validation, to deployment and continuous monitoring. In logistics, it is particularly important to manage:

- drift (changes in demand patterns and disruptions),
- performance monitoring (accuracy, service level, cost KPIs),
- retraining and versioning,
- incident management.

This MLOps layer represents a key managerial instrument, as it enables auditability, reproducibility, and control of changes in operational systems.

AI is increasingly implemented within the framework of digital twin technology, where the physical logistics system is mirrored in a digital model that enables monitoring, prediction, and optimization. Ivanov and Dolgui emphasize that digital twins enable disruption simulation and real-time decision support but require a high level of system integration and interoperability (Ivanov & Dolgui, 2021). The managerial implication is that digital twins are not merely IT projects but platforms for orchestrating decisions and validating AI recommendations.

AI is changing roles in logistics and introducing a new distribution of responsibilities, which requires substantial change management: user training, adaptation of SOP procedures, and redefinition of KPIs. Particularly in multi-partner networks, coordination is crucial. An empirical study by Li et al. shows that the depth of generative AI usage contributes to SCM performance through the mechanism of coordination (Li et al., 2024).

As AI systems influence critical decisions, risk management becomes a central component of implementation. Two dominant risks are:

1. lack of transparency ("black box"),
2. cyber risk and system resilience.

Sadeghi et al. demonstrate that XAI contributes to transparency and agile decision-making, thereby strengthening cyber resilience (Sadeghi et al., 2024). Kosasih et al. further emphasize the role of explainability as a bridge between models and managerial decisions (Kosasih et al., 2024).

An additional layer of managing AI implementation in logistics relates to the development and orchestration of dynamic organizational capabilities that enable continuous adaptation of technological solutions to changing environments. In this context, Dubey et al. show that the effects of AI on supply chain performance are not direct but mediated by organizational capabilities such as analytical agility, data integration, and rapid decision-making (Dubey et al., 2020). These findings suggest that AI implementation must be accompanied by the development of complementary resources and skills, including the ability to interpret and operationalize model outputs in everyday logistics processes.

At the same time, the role of implementation management extends to the institutionalization of AI through standards, procedures, and governance mechanisms that ensure consistency and scalability. Dubey et al. emphasize that organizations that successfully integrate AI into SCM develop formalized routines for using analytical tools and clear protocols for data-driven decision-making (Dubey et al., 2020). In the logistics context, this means that AI implementation cannot remain an isolated initiative but must be embedded in operational and managerial structures to ensure long-term sustainability and strategic value.

In logistics, the success of AI implementation is measured through a combination of operational, cost-related, and sustainability KPIs. The review by Chen et al. confirms the growing importance of sustainability criteria in optimization (Chen et al., 2024). Managerial best practices include controlled experiments before scaling and clearly defined success metrics.

Technical Communication as a Key Factor of Integration and Manageability of AI in Logistics

The integration of artificial intelligence (AI) into logistics systems is often presented in contemporary literature as a technological advancement; however, a closer examination reveals that it is a complex socio-technical process in which technical communication plays a key, yet often implicitly treated, role. Although studies in supply chain management (SCM) and logistics emphasize the importance of data and system integration, they rarely explicitly operationalize the communication mechanisms that enable such integration (Culot et al., 2024; Richey et al., 2023). This creates a gap between the technological capabilities of AI and their actual application in operational environments.

Existing literature predominantly treats AI integration as a problem of system interoperability and data quality, while the communication dimension is reduced to technical specifications (APIs, data models). However, such a reductionist approach overlooks the fact that logistics systems are organizationally distributed and cognitively heterogeneous—different actors (planners, dispatchers, managers) interpret information in different ways. Although Culot et al. identify organizational coordination as a key success factor, they do not elaborate on how such coordination is practically achieved through communication practices (Culot et al., 2024). Similarly, Richey et al. highlight the need for managerial frameworks but without a detailed consideration of the communication artifacts that enable their implementation (Richey et al., 2023).

In the context of digital twins, literature recognizes integration and interoperability as central capabilities but often implicitly assumes that semantic alignment and information exchange are already solved problems. Ivanov and Dolgui emphasize the importance of digital twins for managing disruptions, yet do not sufficiently address the communication challenges arising from the need to align models, data, and interpretations among different actors (Ivanov & Dolgui, 2021). This implicit assumption represents a limitation, as in practice mismatched data semantics and insufficiently documented models frequently lead to implementation failures.

A further critical perspective concerns Explainable AI (XAI), which is often positioned in the literature as a solution to the “black box” problem. Although Kosasih et al. systematize approaches to explainability, the focus remains on technical methods for generating explanations, while the issue of their interpretability in real organizational contexts is insufficiently addressed (Kosasih et al., 2024). Empirical findings by Sadeghi et al. show a positive effect of XAI on agility and resilience, but do not clarify to what extent this effect depends on the quality of communication of explanations to end users (Sadeghi et al., 2024). It can therefore be concluded that explainability alone is not sufficient—its value depends on how it is communicatively structured and adapted to users.

An additional layer of critique relates to the use of generative AI in technical communication. While Reeves and Sylvia highlight both the potential and limitations of GenAI, the literature still lacks sufficient empirical evidence on the long-term effects of its use in high-risk operational environments (Reeves & Sylvia, 2024). Johnson-Eilola et al. show that AI can replicate the form of technical documentation, but not necessarily its functional reliability (Johnson-Eilola et al., 2024). These findings challenge the implicit assumption that automating documentation necessarily leads to efficiency, pointing instead to the risk of “formally correct but operationally incorrect” instructions.

The interorganizational dimension further complicates the issue. Although Li et al. demonstrate that generative AI can enhance coordination in supply chains, their model implicitly assumes the existence of compatible communication structures among partners (Li et al., 2024). In practice, differences in standards, systems, and interests often limit information sharing, implying that the effects of AI depend on institutional and communication frameworks rather than solely on technological capabilities.

Finally, the ethical and governance dimension of AI further underscores the importance of technical communication. Carradini points to the need to redefine professional practices in the context of AI, but the question remains open as to how principles of responsible use are concretely implemented in logistics systems (Carradini, 2024). In this sense, technical communication can be viewed as a mechanism for operationalizing ethics—through transparency, documentation of decisions, and the definition of accountability.

Conclusion

The integration of artificial intelligence into logistics systems represents a structural transformation of management—from traditional operational optimization to the management of complex, data-intensive, and socio-technical systems. Contemporary literature shows that AI contributes to efficiency, agility, sustainability, and resilience of logistics networks through predictive, prescriptive, and automated decision-making mechanisms, as well as through the application of digital twins and generative models. However, technological superiority alone is not sufficient to ensure organizational value.

A key finding emerging from the analyzed literature is that the success of AI implementation depends on three interrelated factors: (1) high-quality integration of data and systems, (2) organizational coordination and change management, and (3) structured technical communication that enables explainability, transparency, and control. Without clear documentation standards, semantic interoperability, XAI mechanisms, and model lifecycle management, AI systems remain fragmented and difficult to manage.

In this context, technical communication is positioned as both an integrative and control infrastructure of AI in logistics. It enables algorithmic decisions to be understandable, verifiable, and aligned with operational goals, regulatory requirements, and ethical principles. Particularly in the context of generative AI and digital twin technologies, communication standards become a prerequisite for trust and institutional legitimacy. Therefore, it can be concluded that contemporary logistics management involves not only the application of advanced algorithms, but also the management of their integration through clearly defined processes, responsibilities, and communication protocols. The synergy between AI and technical communication represents the foundation for a sustainable, transparent, and scalable transformation of logistics systems in a digital environment.

Conflict of interests

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Data Availability Statement

The data supporting the findings of this study are available from the corresponding author upon reasonable request.

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