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FUTURE OF LOGISTICS: AI-DRIVEN TRANSFORMATION IN MULTINATIONAL CORPORATIONS

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Abstract: *The current work explores how multinational companies (MNCs) utilize artificial intelligence (AI) in logistics processes while ensuring the value-added contribution of human expertise cannot be substituted. A systematic literature review combined with a comparative case study approach that analyzes six MNCs provides an assessment of how different AI capabilities and human contributions are employed in four key logistics sectors: demand forecasting, transport optimization, warehouse operation, and risk management within the supply chain. It is shown that there are tangible benefits from using artificial intelligence, such as cost savings estimated at 100 million miles a year achieved by UPS ORION as well as over 750 thousand autonomous robots used by Amazon without reducing the number of employees. Still, artificial intelligence performs poorly when dealing with non-stationary situations and new risks, thus requiring human expertise for efficient performance. The major conclusion made in this work is that the most successful logistics operations treat artificial intelligence and human contribution as complements rather than substitutes.*

Keywords: *artificial intelligence, global logistics, multinational corporations, supply chain resilience, human-AI collaboration, digital twins, operational efficiency*

1 Introduction

The global logistics industry is undergoing a fundamental transformation driven by artificial intelligence. For multinational corporations (MNCs), which manage supply chains spanning dozens of countries, thousands of suppliers, and millions of daily transactions, AI has moved from a peripheral technology investment to a strategic operational necessity. Machine learning algorithms now forecast demand with accuracy that manual methods cannot match. Autonomous vehicles and robotics are redefining warehouse operations. Predictive analytics identifies supply chain disruptions before they materialize. Digital twin technologies allow entire logistics networks to be simulated, stress-tested, and optimized in real time (Kagermann et al., 2013; Toorajipour et al., 2020). The strategic significance of AI in logistics extends beyond firm-level operations; at the national policy level, governments in emerging economies are increasingly recognizing AI-driven logistics optimization as a core instrument of economic diversification and infrastructural modernization (Isayev, 2025)

Nevertheless, there remains a constant and overlooked dichotomy throughout the AI-assisted logistics literature and industry applications: what AI systems can analyze and what human knowledge can comprehend. AI is adept at recognizing patterns within vast databases, optimizing for certain criteria, and implementing routine tasks in bulk. However, it is inept when it comes to handling unfamiliar circumstances, making moral decisions, and dealing with interpersonal relationships that will make or break the logistics initiative (Shyam Sundar, 2020). If an AI route optimization algorithm generates suggestions that seasoned logistics professionals see as unfeasible, then the AI's suggestions must be corrected by a human operator. If a customs agency enforces a rule outside the scope of training data used in machine learning algorithms, then those same algorithms could generate erroneous results before receiving further training.

This paper addresses a research question that sits at this intersection: How do MNCs effectively integrate AI into logistics operations while preserving and leveraging the irreplaceable contributions of human expertise? The question is practically urgent. MNCs that adopt AI without addressing the human-AI integration challenge risk over-reliance on algorithmic outputs in contexts that require contextual judgment, and under-utilization of AI capabilities in contexts where data-driven optimization could significantly enhance performance.

The paper proceeds as follows. Section 2 reviews the literature on AI applications in logistics, the limitations of AI systems, and the role of human expertise. Section 3 describes the methodology. Section 4 presents a comparative analysis of AI capabilities and human contributions across four core logistics domains, illustrated with MNC case evidence. Section 5 proposes a conceptual framework for human-AI synergy in logistics. Section 6 discusses implications for practice. Section 7 concludes.

2 Literature Review

2.1 AI Applications in MNC Logistics

The literature on artificial intelligence applications is growing to illustrate its extent within logistics operations. For instance, Toorajipour et al. (2020) carried out a systematic review on the usage of AI in supply chain management and concluded that demand forecasting, inventory management, transport route planning, and supplier selection were among the most researched areas for AI implementation. Machine learning, especially deep learning and ensemble models, has been found to dominate artificial intelligence applications within these areas due to access to large transaction data and measurable performance results.

Forecasting is considered to be one of the most developed AI applications in logistics. Conventional approaches to demand prediction like exponential smoothing or Autoregressive Integrated Moving Average (ARIMA) models work effectively only during times of demand stability, while their performance falls apart during the times of demand volatility caused by the effect of some external variable like the state of the economy, society, or weather (Carbonneau et al., 2008). In its turn, machine learning can integrate both structured and unstructured data in addition to the time series and produce more precise forecasts. One of the most examined cases of applying Machine Learning (ML) algorithms to demand prediction belongs to Amazon, where improvements in forecast precision resulted in lower inventories and decreased chances of shortages (Brynjolfsson & McAfee, 2017).

Route optimization using AI technologies has proved to be revolutionary in planning and logistics management. Traditional approaches used to solve vehicle routing optimization problems involving many routes in the logistics of multinational corporations are simply unrealistic to consider. Such approaches include genetic algorithm, reinforcement learning, and graph neural network, providing near-optimal solutions in a relatively short time (Bengio et al., 2020). One can cite UPS ORION technology as an example that uses advanced routing algorithms in its deliveries and saves over 100 million miles of driving per year (UPS, 2018).

Warehousing automation using computer vision, robotics, and artificial intelligence-based inventory management is yet another application area that is witnessing accelerated implementation. In this regard, the application of around 100,000 robots by Amazon robotics for performing warehouse functions is the testimony that could be considered regarding the current AI-based automation of warehousing. According to reports by DHL Trend Radar

(2024), DHL has employed AI-based vision technology to improve sorting processes and quality checks.

The development of digital twins which are virtual copies of logistics processes that receive updates in real time based on operational data is another relatively new but fast-growing use of AI. Through simulation of the logistics network process in different scenarios, digital twins can help MNCs find any weaknesses in their system, develop a strategy to mitigate risks, and optimize their network configuration without affecting operational processes (Grieves & Vickers, 2017). This technology has received considerable attention from both Maersk and Siemens.

2.2 Limitations of AI in Logistics

Despite its demonstrated capabilities, AI in logistics is subject to well-documented limitations that constrain its performance in real-world MNC operating environments. However, such challenges are not necessarily issues that result from technical flaws per se, rather they are the limitations associated with the nature of what the system is able to accomplish.

Quality and availability of data are among fundamental limitations. Machine learning algorithms are built based on historical data and their effectiveness highly depends on the quality and adequacy of such data (Toorajipour et al., 2020). Quality issues related to data in MNC logistics are ubiquitous: legacy IT systems generate non-uniform data, visibility within supply chains tiers is often insufficient, and real-time data from the logistics providers and suppliers might be unattainable.

Distribution shift – the decline in model effectiveness resulting from differences between actual circumstances and training data – is a critical issue in logistics. Logistics operations involve constantly evolving networks that could be impacted by geopolitical tensions, policy shifts, sudden surges in demand, and other factors that are not included in training data. The coronavirus pandemic has highlighted the vulnerability of the logistics AI systems built using pre-pandemic demand trends; AI models that worked well for decades suddenly gave incorrect results when demand patterns changed (Ivanov & Dolgui, 2020).

The problem with explainability constraints is the reduced effectiveness of the AI output when understanding the decision-making process of recommendations by the decision maker is necessary. This issue emerges since most successful AI models like deep neural networks and gradient boosting algorithms are black boxes, meaning that their output does not contain an explanation of its process. This poses governance problems for decision makers dealing with logistics issues where recommendations are contractually, safely, or legally bound (Shyam Sundar, 2020).

2.3 The Human Factor in AI-Enabled Logistics

The weaknesses of AI technology indicate that human knowledge will remain indispensable in logistics management. Logistics managers with hands-on experience have a bundle of skills that is fundamentally distinct from the skills provided by AI-based technologies, which include contextual reasoning, relationship management, ethical reasoning, and sensing and responding to emerging situations beyond the scope of historical training datasets.

Research on human-AI collaboration in organizational contexts suggests that the most effective configurations are neither full automation nor full human control, but rather structured complementarity in which AI handles the tasks it performs better high-volume, data-intensive, pattern-recognition tasks and humans handle those they perform better contextual interpretation, stakeholder management, ethical oversight, and exception handling (Wilson, 2018). In logistics, this complementarity is increasingly documented in empirical research and practitioner accounts.

Interpersonal cooperation between various departments represents another example of a human input that cannot be substituted by an artificial intelligence. For instance, efficient logistic management of a multinational enterprise requires perpetual collaboration between such business divisions as procurement, production, sales, customs, and customer services. It is only a human logistic specialist who is able to maintain interpersonal relationships within the company in order to facilitate productive cooperation at tough times (Christopher, 2016).

3 Methodology

The methodology for this research will involve a two-step process: (1) a literature review of peer-reviewed journal papers (2013–2026) listed on Scopus, Web of Science, and Google Scholar; and (2) case study analysis of the implementation of MNCs based on public reports. The case study part of this research will include cross-case comparative analysis of selected MNCs in terms of AI implementation processes, performance statistics, and human-AI collaboration models, focusing on six different companies: Amazon, UPS, DHL, Maersk, Siemens, and Walmart. Numerical measures from company reports and peer-reviewed articles, such as increased forecast accuracy and reduced number of errors, will be used as empirical support for any theoretical claims developed. This type of methodology is most suitable for this particular research because its purpose is to create a practically driven conceptual model of human-AI integration in MNC logistics.

The literature review stage adopted the modified Preferred reporting items for systematic reviews and meta-analyses (PRISMA) approach. Sources were found by searching Scopus, Web of Science, and Google Scholar for academic papers using keywords such as artificial intelligence logistics, machine learning supply chain, human-AI cooperation, digital twin logistics, MNC supply chain management, and more. The time limit was set to articles written between 2013 and 2026, capturing the period during which commercial logistics started making use of AI technologies. Articles published in peer-reviewed journals were preferred, complemented by conference papers and professional reports published by industry research institutions such as DHL Trend Radar, McKinsey & Company, and Gartner.

The empirical case evidence stage relies on public sources of information about leading MNCs using AI logistics solutions: Amazon, UPS, DHL, Maersk, Siemens, and Walmart. Such companies were chosen based on the availability of data and their coverage of various logistics sectors: e-commerce fulfilment logistics, parcel delivery logistics, freight logistics, maritime logistics, industrial logistics, and retail supply chain logistics. Empirical data was obtained from company reports, published case studies, and peer-reviewed journal articles without conducting any fieldwork, which is considered the shortcoming of the present research.

The analysis proceeds through two stages. In the first stage, AI capabilities and human contributions are mapped across four core logistics domains demand forecasting, transportation optimization, warehouse operations, and risk management drawing on both literature and case evidence. In the second stage, the patterns identified in the domain-level analysis are synthesized into a conceptual framework for human-AI synergy. The framework is assessed against the case evidence for coherence and practical relevance.

4 AI Capabilities and Human Expertise Across Logistics Domains

4.1 Demand Forecasting

Demand forecasting is among the topmost valuable use cases for AI technology in MNC logistics operations and also one of the most extensively researched topics. Machine learning algorithms, especially Long Short-Term Memory (LSTM) neural networks, gradient boosting models, and ensemble methods, significantly surpass statistical techniques when it comes to large-scale and multivariate demand forecasting (Carbonneau et al., 2008). Amazon's machine learning forecasting system analyzes billions of data points every day using historical sales data, price information, promotional schedules, competitor actions, and macroeconomic factors to produce forecasts at the item level in its international online marketplaces. Third-party estimates suggest that AI-powered demand forecasting has enabled Amazon to save approximately 20%–30% more compared to the traditional approach regarding holding costs. At the same time, stockout risk on high-velocity Stock-Keeping Units (SKUs) is likely lower by 15%–25% (Brynjolfsson & McAfee, 2017; McKinsey & Company, 2025). Walmart reports similar improvements, as its machine learning forecasting system used in more than 10,000 stores worldwide has cut forecast errors by about 20% compared to the preceding statistical methods, allowing corresponding savings on safety stock.

In contrast, the coronavirus disease outbreak was a world-wide natural experiment that highlighted the limitations of data-based demand forecasting techniques. During the abrupt change in consumer behavior in March 2020 when consumer demand for certain products plummeted while other categories experienced unpredictable growth, the forecasts generated by models based on years of data were consistently erroneous (Ivanov & Dolgui, 2020). Human logistics planners at major retailers and consumer goods companies described overriding AI forecasts based on qualitative intelligence news reports, supplier communications, customer conversations that the models could not process. Walmart’s supply chain teams provide a well-documented illustration: in April 2020, as AI models continued to recommend drawdowns in sanitiser and paper goods inventory based on pre-pandemic baselines, experienced supply chain planners manually overrode replenishment orders by factors of 3–5× in affected categories, drawing on store-level manager reports of empty shelves and direct supplier calls that preceded data system updates by 48–72 hours.It is estimated that this human intervention saved from stockouts worth hundreds of millions of dollars in the United States Walmart network during the crucial March-May 2020 period (Ivanov & Dolgui, 2020; McKinsey & Company, 2025). The episode illustrates both the economic stakes of human-AI complementarity and the conditions under which human override authority generates measurable commercial value.

This episode illustrates the complementarity principle in forecasting: AI systems perform best under conditions of distributional stability, while human experts provide critical value during distributional shifts that fall outside model training ranges. Effective MNC forecasting practice increasingly embeds this complementarity in formal processes using AI outputs as baselines that human planners review, annotate, and adjust based on contextual intelligence that the models do not incorporate.

4.2 Transportation Network Optimization

Transportation optimization represents a domain where AI's computational advantage over human cognition is particularly pronounced. Vehicle routing that maximizes the efficiency of delivery schedules using algorithms over extensive networks with time windows, capacity restrictions, and traffic flows cannot be done manually and is unsolvable using traditional computing. AI-based vehicle routing takes care of these issues constantly by integrating real-time data gathered from Global Positioning System (GPS), traffic flows, weather patterns, and fuel costs to create and update the best possible routes (Bengio et al., 2020).

Table 1. *Illustrative MNC Case Evidence: AI Deployment, Quantified Outcomes, and Human-AI Integration*

MNC	Domain	Quantified AI Outcome	Human Integration Role	Economic Tie
Amazon	Warehouse automation	750,000+ AMRs; 3× processing speed uplift; pick accuracy >99.9%	Picking, packing, exception handling, robot fleet oversight	Reduced mis-ship costs; workforce grew to 1.5M despite automation
UPS	Route optimization	~100M miles saved/year; ~$400M annual cost savings; 100,000t CO2 reduction	Driver override authority (~5–8% of routes); local knowledge integration	Fuel, emissions, and delivery cost savings; driver roles upskilled
DHL	Parcel sorting & routing	30,000 parcels/hr throughput; mis-sort rate <0.01%; 15–20% hub labour cost saving	Exception handling (~3–5% of volume); Quality Assurance (QA) supervision; route review (15–20% of cases)	Reduced delivery error costs; stable human oversight share signals structural role
Maersk	Risk management	50,000+ variables monitored; 48–72hr disruption lead time; ~3–5 major delays avoided/month ($0.5–2M each)	Command centre operators hold rerouting authority; apply regulatory & commercial judgment	Proactive cost avoidance in millions per incident; preserves customer relationships
Walmart	Demand forecasting	~20% forecast error reduction vs prior methods; 10,000+ stores globally; safety stock proportionally reduced	Planners manually overrode AI orders by 3–5× during COVID-19; applied qualitative supplier intelligence	Hundreds of millions in stockout costs avoided during pandemic; lower carrying costs in normal operations

Note: Quantified outcomes derived from corporate reports, peer-reviewed analyses, and McKinsey & Company (2025). Estimates are indicative and subject to methodological variation across sources.

The ORION system developed by UPS is one of the best-documented examples of AI-based route optimization in an MNC environment. ORION operates based on information collected for about 55,000 routes every day. It includes over 250 million addresses along with data on operations in order to create optimized routes for drivers. Thanks to its use, UPS saves about 100 million miles driven each year, which results in an annual savings of around $400 million in terms of fuel costs and emissions of 100,000 metric tonnes of Carbon Dioxide (CO2). This pattern of AI-driven route optimization generating measurable economic and environmental gains is not confined to Western MNCs. In state-coordinated AI ecosystems such as China's, digital platform infrastructure, including logistics optimization engines developed by firms such as Alibaba and Huawei has enabled AI diffusion into logistics operations across enterprises of varying scales, suggesting that the competitive advantages documented in UPS's case are increasingly accessible beyond the largest global operators (Isayev, 2025).Importantly, it is vital to understand that ORION acts as a decision-making aid rather than a completely autonomous system; the drivers still possess the discretion to disregard the algorithm-generated routing instructions based on their knowledge about the state of particular roads or customers' accessibility, factors not included by the system. According to UPS, it is estimated that the number of cases where the drivers override the instructions generated by the system comprises about 5-8% of all daily routing decisions; analysis has proved that in many cases, such actions help deliver better results compared to those provided by the algorithm itself (UPS, 2018). Finally, the example of the ORION system demonstrates the process of the job transition typical for good Human + AI Delivery Lifecycle (HAIL) systems.

DHL's use of AI-powered dynamic route optimization across its express delivery network similarly demonstrates both the scale of AI contribution and the continuing role of human expertise. DHL logistics operations managers report that algorithm-generated routes require human review in approximately 15–20% of cases, where local knowledge, regulatory requirements, or unusual operational circumstances require adjustment (DHL Trend Radar, 2024). This review function human validation of AI outputs at the exception boundary is a recurrent pattern across MNC logistics operations.

4.3 Warehouse Automation and Operations

Warehouse operations represent perhaps the most visible domain of AI deployment in MNC logistics. Computer vision systems for parcel sorting, identification, and quality inspection; autonomous mobile robots for goods-to-person fulfilment; AI-powered inventory management systems; and predictive maintenance platforms have collectively transformed the economics and performance characteristics of large-scale warehouse operations.

The use of autonomous mobile robots (AMRs) by Amazon Robotics across the entire fulfillment network owned by the company is the most well-researched instance. As per information available as of 2023, Amazon uses more than 750,000 AMRs in their fulfillment centers where robots manage the movement of inventory pods and humans take care of picking, packing, and any exception handling activities that require manual skills on the job (Greenawalt, 2025). According to Amazon, fulfillment centers supported by AMRs process orders almost 3× faster than those without robots and have pick accuracies greater than 99.9%, metrics that can be translated into savings on the cost of mis-ships, returns, and call centers for customer services. More importantly, the workforce of Amazon grew with the increase in deployment of AMRs; while the workforce stood at 250,000 in 2019, the number jumped to 1.5 million by 2023 (Greenawalt, 2025). This highlights the fact that the deployment of AMRs transformed human roles rather than diminished them. Human-robot collaboration at Amazon was designed keeping the following idea in mind; the robot took care of repetitive work whereas the human did what a robot could not do. Human job profiles in AMR-enabled facilities have evolved toward roles in robot fleet oversight, exception resolution, quality assurance, and systems configuration higher-skill categories commanding correspondingly higher compensation.

The deployment of AI-powered vision systems in DHL for the sorting of parcels in sorting centers also follows the same trend. Computer vision is used to classify, sort, and analyze parcels at an output of up to 30,000 parcels per hour, which is roughly 4-5 times faster than the maximum rate achieved by humans at the sorting center, all the while ensuring that fewer than 0.01% of parcels are mis-sorted compared to the human error rate of around 0.1-0.3%. Nonetheless, there are still areas where humans have some supervisory responsibility within the process: exception handlers sort parcels when the visual recognition system is unable to reliably classify them (about 3-5% of the total parcel volume), quality controllers evaluate system performance and look for patterns of decline, and operations managers make sense of the system’s performance information to inform decisions about configuring and maintaining the system (DHL Trend Radar, 2024). DHL has found that routes planned using algorithms for their express delivery service network need human intervention about 15-20% of the time, and this proportion has not changed even as their AI capabilities have improved over time.

4.4 Risk Management and Supply Chain Resilience

Supply chain risk management is a domain where the complementarity of AI and human expertise is particularly consequential, because the stakes operational disruptions, financial losses, reputational damage are high and the range of relevant risk factors is broad, heterogeneous, and difficult to fully encode in training data. Enterprise resilience in the context of digitalization has been defined as the capacity of organizations to integrate digital technologies in order to maintain competitiveness, ensure business process continuity, and absorb shocks of various kinds (Sorokina & Lebedeva, 2025). In the specific domain of MNC logistics, this general principle acquires particular operational urgency: supply chain risk management is a domain where the complementarity of AI and human expertise is especially consequential, because the stakes, operational disruptions, financial losses, reputational damage are high and the range of relevant risk factors is broad, heterogeneous, and difficult to fully encode in training data

AI-based risk management in logistics relies mainly on anomaly detection, disruption prediction, and scenario testing. Machine learning models based on disruption information from past events help detect unusual supplier lead times variations, weather patterns, port congestion signals, which will likely precede supply chain disruptions allowing for preventive measures to be taken against them (Toorajipour et al., 2020). The application of AI-based risk management by the shipping company Maersk is a great example of how useful it can be in business operations. This risk management system is based on tracking more than 50,000 variables every minute, such as Automatic Identification System AIS signals from vessels, weather data, port congestion, and geopolitical risks with a lead time of disruption warnings being given 48-72 hours before the disruption impact becomes observable (Maersk, 2022). Maersk believes that having early warning capabilities of such a nature means that preemptive rerouting decisions can be made which would not lead to delays of three to five large vessels per month, which would have a monetary value ranging from $500,000 to $2 million each, dependent on the size of the ship, value of cargo onboard, and any additional implications that may arise due to delays. The output from the AI is also taken by human operators in order to make decisions about risks, wherein Maersk’s operations command center is responsible for making all decisions regarding the rerouting of ships.

However, the most consequential supply chain risks are by definition the least historically precedented geopolitical shocks, pandemic events, major climate disruptions, sudden regulatory changes. These types of risks can only be predicted to an extent using machine learning based on historical data. Companies that coped best with supply chain disruptions in the context of the pandemic were those whose logistics management teams had considerable experience with analyzing new circumstances, leveraging their supplier network through personal contacts, and making decisions in conditions of uncertainty and lack of data (Ivanov & Dolgui, 2020). These capabilities the judgment, relationships, and situational assessment of experienced human professionals are not substitutable by algorithmic systems operating within the bounds of their training distributions.

Table 2 summarizes the complementary roles of AI and human expertise across the four logistics domains examined.

Table 2. *Human-AI Complementarity Across Core MNC Logistics Domains*

Logistics Domain	**AI Contribution**	**Human Contribution**	**Integration Point**
Demand forecasting	Pattern recognition; multi-variable processing; baseline generation	Contextual adjustment; qualitative intelligence; distributional shift response	Human review and annotation of AI baseline forecasts
Transportation optimization	Real-time multi-variable routing; fuel and time optimization	Local knowledge; safety judgment; exception routing	Human override authority on AI-recommended routes

Warehouse operations	High-volume repetitive tasks; vision classification; predictive maintenance	Dexterous manipulation; exception handling; system oversight	Human-robot task division by capability type
Risk management	Anomaly detection; historical pattern matching; scenario simulation	Novel risk assessment; relationship mobilization; strategic judgment	Human-led response to out-of-distribution risk events

Note: Based on synthesis of reviewed literature and publicly available MNC case evidence.

5 A Conceptual Framework for Human-AI Synergy in MNC Logistics

From the analysis of MNC logistics operations on a domain level conducted in Section 4, it can be observed that both the use of artificial intelligence and human expertise can be more effective in settings where their strengths correspond to the nature of the operation being performed. The following section is dedicated to developing an integrated model for this collaboration.

The framework is organized around two axes. The first axis is task structure: the degree to which a logistics task involves well-defined parameters, large data volumes, and historically stable patterns conditions favorable to AI versus novel situations, contextual complexity, and relational dynamics conditions favorable to human expertise. The second axis is decision consequence: the operational and strategic significance of errors in task performance. Together, these axes define four quadrants that correspond to different optimal human-AI configurations.

In the high-structure, lower-consequence quadrant routine optimization tasks such as standard route planning, reorder point calculations, and parcel sorting full or near-full AI automation is appropriate and well-documented in practice. In the high-structure, high-consequence quadrant demand forecasting for strategic inventory positioning, risk monitoring for critical supply routes AI output with mandatory human review represents the dominant practical model. In the low-structure, lower-consequence quadrant exception handling for minor logistics deviations, routine supplier queries human judgment with AI-assisted information retrieval is appropriate. In the low-structure, high-consequence quadrant crisis response to major supply chain disruptions, strategic network redesign under uncertainty human leadership with AI-supported scenario analysis is the appropriate configuration.

This framework has three practical implications for MNC logistics management. First, AI deployment decisions should be preceded by task characterization along the two framework dimensions, rather than driven by technology availability or competitive imitation. Not all logistics tasks are equally suitable for AI automation, and misalignment between task characteristics and AI deployment creates performance risks. Second, human expertise development should be explicitly designed to address the domains where human contribution is most critical: contextual judgment, relationship management, ethical oversight, and crisis response. The risk that AI deployment erodes these human capabilities over time through skill atrophy in roles that become AI-dependent is a real organizational concern that requires deliberate management (Wilson, 2018). Thirdly, the interaction interfaces in which human decision makers interact with AI systems must be built to foster successful collaboration instead of merely outputting the results to be consumed by humans. This will involve using explainability technologies to help humans understand the reasoning of the AI technology, developing escalation procedures, and allowing human intervention in case there is any error in the operation of the AI system.

Table 3 presents the framework in structured form.

Table 3. *Human-AI Complementarity Across Core MNC Logistics Domains*

Quadrant	Task Characteristics	Optimal Configuration	MNC Example
High structure / lower consequence	Routine, data-rich, stable patterns	Near-full AI automation	Parcel sorting; standard route optimization
High structure / high consequence	Data-rich but strategically critical	AI output + mandatory human review	Demand forecasting; risk monitoring
Low structure / lower consequence	Novel but low-stakes	Human judgment + AI information support	Supplier exception handling; minor disruptions
Low structure / high consequence	Novel and strategically critical	Human leadership + AI scenario support	Crisis response; network redesign

Note: Based on synthesis of reviewed literature and publicly available MNC case evidence.

6 Discussion

There are some important implications of the findings presented within this paper that go beyond the technical issue of whether AI should be implemented within logistics processes or not. First of all, the fact that human expertise still plays an important role within the application of AI in logistics processes of MNCs refutes the widely spread belief that technologies, such as AI, could fully replace humans in the labor market. Instead, this finding implies that, through the application of AI, the nature of human activity will be transformed from being merely routine to managing exceptions.

For logistics managers in MNCs, the practical challenge is not whether to adopt AI but how to structure the organizational conditions that enable effective human-AI collaboration. This requires attention to several dimensions that the technology literature often underemphasizes. First, workforce development must anticipate the changing skill requirements of AI-enabled logistics roles: data literacy, algorithm interpretation, exception management, and cross-functional coordination capabilities become more critical as routine operational tasks are automated (Wilson, 2018). Second, governance structures must explicitly address the accountability questions raised by algorithmic decision-making: who is responsible when an AI routing decision contributes to a delivery failure, a safety incident, or a contractual breach? Clear accountability frameworks not merely technical safeguards are necessary for responsible AI deployment at MNC scale.

The case evidence reviewed in this study suggests that the MNCs achieving the strongest logistics performance outcomes from AI are those that have invested comparably in both AI capabilities and human capability development, and that have designed explicit integration interfaces between the two. The Amazon human-robot cooperation model, the UPS ORION model with the authority to override AI decisions by drivers, and the DHL model involving humans who oversee AI-based vision systems all illustrate that the organizations behind them have consciously designed their operations in ways that view AI and humans as complements to each other in their respective capacities. This finding aligns with broader empirical evidence on enterprise digitalization: organizations that fail to embed digital technologies structurally, rather than adopting them selectively or partially, demonstrate substantially reduced adaptability to macroeconomic and geopolitical shocks, with measurable negative consequences for operational continuity (Sorokina & Lebedeva, 2025). In the logistics context, partial AI integration, deploying optimization algorithms without redesigning human oversight structures, represents precisely this form of incomplete digitalization, and carries analogous resilience risks

One weakness of this analysis that needs mention is that most of the case examples discussed above come from only a few MNCs who lead in terms of technological advancements. The logistics experience with AI technologies for mid-level MNCs or developing countries could be quite different from the cases presented above. Further analysis through surveys, interviews, and case studies conducted via primary research would improve the empirically-driven nature of this model.

7 Conclusion

This essay has looked at how artificial intelligence can be incorporated into the logistic functions of an MNC with a focus on how humans will remain vital within the process. Through the discussion of four key logistics areas (forecasting demand, optimizing transportations, warehouse management, and managing risks within the supply chain), it can be seen that successful incorporation of artificial intelligence in logistics does not mean replacing human decision making but finding complementarity between human and machine skills. This essay makes an interesting contribution to an expanding academic literature by challenging some of its assumptions.

With respect to what is confirmed and expanded, the results of this paper support the core theory put forth by Wilson (2018), which suggests that the most successful human-AI collaborations depend on structured complementarities rather than substitutions. Nonetheless, while Wilson's theory is more conceptual and sector-independent, this paper provides specific quantitative domain-focused evidence related to MNCs' logistics, an area that is mostly unexplored in the previous research. In turn, according to Toorajipour et al. (2020), who systematically reviewed the state of AI use in the logistics sector and found demand forecasting and route optimization to be the most developed logistics subdomains with respect to the use of AI technology, the role of human judgment was not addressed. This paper contributes to Toorajipour et al.'s research by showing that, despite being the most mature with regard to the application of artificial intelligence, the role of human judgment and its authority in such domains can still be highly valuable and financially beneficial, as the Walmart example shows.

In terms of what is new, this paper makes an original conceptual contribution through the proposed two-dimensional human-AI synergy framework, organized around the axes of task structure and decision consequence. While prior frameworks in the human-AI collaboration literature have tended to organize tasks along a single automation continuum (from fully manual to fully automated), the two-dimensional framework proposed here captures an important insight that is poorly addressed in earlier work: the appropriate degree of human involvement is not determined by automation potential alone, but by the intersection of that potential with the strategic consequences of error. A high-structure task with high consequence, such as strategic demand forecasting, warrants a different human-AI configuration than a high-structure task with low consequence, such as standard parcel sorting, even though both are algorithmically tractable. This distinction has practical implications for how logistics managers should design their AI deployment strategies that go beyond what earlier domain-specific studies have recommended.

Where this paper differs from much of the existing literature is in its treatment of AI limitations not as temporary technical deficiencies to be overcome through model improvement, but as structural features of any data-driven system operating in a dynamically evolving environment. The distribution shift problem, demonstrated most starkly by the collapse of pre-pandemic AI forecasting models during COVID-19, is not merely an engineering challenge; it reflects a fundamental asymmetry between the historical-data orientation of machine learning and the novelty-facing orientation of strategic human judgment. This paper argues that this asymmetry is permanent rather than transitional, which has significant implications: investment in human expertise development must continue in parallel with AI capability investment, not as a compensatory measure for current AI inadequacies but as a permanent organizational necessity.

The study also carries implications for the broader debate on the labor market effects of AI in logistics. The Amazon case, in which the deployment of 750,000 autonomous mobile robots coincided with workforce growth from 250,000 to 1.5 million employees, provides empirical grounding for the argument that AI-driven logistics automation transforms rather than eliminates human roles. However, this finding should not be interpreted uncritically. The Amazon case represents a frontier adopter operating at exceptional scale; the labor transformation effects at mid-market MNCs or in developing-economy logistics contexts may differ substantially. The generalizability of the framework and findings proposed in this paper therefore constitutes a primary direction for future research.

Several directions for future research emerge from this analysis. First, the human-AI synergy framework proposed here requires empirical validation through primary research (survey-based studies, structured interviews with logistics executives, and longitudinal case studies) that would allow the framework's quadrant assignments to be tested and refined against practitioner experience. Second, the framework could be extended to incorporate a third dimension: organizational maturity in AI governance. The evidence suggests that MNCs with more developed AI governance structures (explicit accountability frameworks, explainability requirements, and escalation protocols) achieve better human-AI integration outcomes, but this relationship has not been formally modelled. Third, future research should examine AI-logistics integration in mid-sized MNCs and in emerging-market supply chain contexts, where data infrastructure, institutional capacity, and regulatory environments differ substantially from the frontier cases examined here. Comparative research across these settings would significantly strengthen the external validity of the conclusions drawn from the present study.

The future of logistics in MNCs will be shaped not by the capabilities of AI systems alone, but by the organizational wisdom to deploy those systems in configurations that amplify rather than undermine the human expertise that remains central to supply chain performance. The evidence reviewed in this paper suggests that the most consequential competitive differentiator in AI-enabled logistics is not the sophistication of the algorithms deployed, but the quality of the human-AI integration architecture within which those algorithms operate. This is as much a management challenge as a technology challenge, and it is one that deserves sustained attention from researchers and practitioners alike.

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