

RESEARCH PAPER

AI-Augmented logistics and strategic evaluation: an extended ELECTRE Tri-Neutrosophic framework for DHL's global transformation

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ABSTRACT

Goal: The objective of this research is to evaluate DHL's transformation into an AI-augmented logistics provider. The study aims to determine how strategic initiatives can be prioritized under uncertainty, ensuring resilience, scalability, sustainability, and workforce adaptation in global logistics operations.

Design / Methodology / Approach: The study applies the Extended ELECTRE Tri method enriched with neutrosophic uncertainty modeling. Techniques include entropy-based weighting, neutrosophic closeness, outranking flows, and Monte Carlo sensitivity analysis. Expert judgments were collected and modeled using Interval-Valued Neutrosophic Sets to capture hesitation, divergence, and indeterminacy in evaluations.

Results: The analysis classified cybersecurity platforms, autonomous orchestration, and sustainability routing

as high-priority initiatives, demonstrating stability under uncertainty and alignment with operational and ecological goals. Predictive workforce augmentation and agentic AI communications were assessed as moderate priority, reflecting contextual dependence and variability in expert judgments.

Limitations of the investigation: The study focuses exclusively on DHL, limiting generalizability across the logistics sector. Reliance on expert judgments introduces potential bias, and the criteria set reflects DHL priorities rather than evolving conditions. Proprietary data constraints restricted empirical validation, and classification outcomes remain sensitive to threshold selection despite robustness checks.

Practical implications: The findings provide DHL and similar operators with a structured framework to selectively scale robust initiatives while cautiously adapting those with weaker stability. The approach supports evidence-based decision-making for digital transformation strategies in logistics under uncertainty.

Originality / Value: This research contributes to logistics literature by advancing multi-criteria decision-making through the integration of neutrosophic uncertainty modeling. It demonstrates the applicability of the Extended ELECTRE Tri framework to real-world logistics transformation, offering a replicable model for global operators navigating AI adoption and digital resilience.

Keywords: AI-augmented logistics; ELECTRE Tri; Neutrosophic sets; DHL transformation; Multi-criteria decision-making.

1 INTRODUCTION

Artificial intelligence (AI) has become a central driver of transformation in global supply chain management, influencing how organizations design, operate, and evaluate logistics systems. In recent years, the convergence of robotics, predictive analytics, and agent-based AI has repositioned logistics from a primarily operational function to a strategic domain that shapes resilience, adaptability, and customer responsiveness (Smyth et al., 2024; Al-Hourani and Weraikat, 2025; Balan, Kumar and Raj, 2025). DHL provides a relevant case, having progressed from pilot

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deployments to large-scale integration across warehousing, distribution, and communication systems. This shift reflects the broader recognition that logistics must sustain viability in environments characterized by complexity and uncertainty rather than focus solely on efficiency (Ibrahim, Pereira and Caldas, 2024; Petropoulos et al., 2026).

The global logistics sector is increasingly volatile due to fluctuating demand, geopolitical disruptions, and sustainability requirements. Traditional supply chain models, which relied on deterministic planning and manual coordination, have shown limitations in addressing these challenges (Kumar, Mishra and Lamba, 2025; Song et al., 2026). AI augmentation introduces new capabilities: predictive modeling supports proactive responses to demand variability, robotic automation improves throughput and safety, and orchestration platforms facilitate collaboration between human and machine actors. Ren et al. (2024) describe supply chains as “intertwined networks” whose resilience depends on adaptive orchestration, a view consistent with DHL's ongoing transformation.

Within this context, DHL's adoption of autonomous mobile robots (AMRs), vision-enabled systems, and AI-driven orchestration platforms illustrates the evolution of logistics operations into intelligent ecosystems. Automated warehousing tasks such as unloading, picking, and intra-warehouse transport reduce human exposure to hazardous environments while improving accuracy (Kadmiri et al., 2026). Predictive analytics embedded in demand forecasting enable DHL to anticipate seasonal fluctuations, adjust capacity dynamically, and reduce reliance on temporary staffing. These developments demonstrate how AI augmentation redefines established production management criteria, including efficiency, reliability, and scalability (Valencia-Arias et al., 2025; Raina et al., 2026).

Beyond operational improvements, DHL's transformation raises questions of strategic evaluation and prioritization. As AI initiatives expand across workflows, decision-makers must identify which technologies merit global scaling, which require further adaptation, and which remain secondary. Criteria such as cybersecurity resilience, sustainability optimization, and workforce augmentation have become central to this evaluation. AI-driven anomaly detection and blockchain-enabled traceability strengthen data integrity, while optimization algorithms reduce energy consumption and carbon emissions. Human-robot collaboration models reshape workforce dynamics, requiring new competencies while reducing repetitive tasks. These criteria illustrate the multidimensional nature of AI transformation, where operational efficiency must be balanced with resilience, sustainability, and human factors.

To address this complexity, structured decision-making frameworks are required. Classical multi-criteria decision-making (MCDM) methods often struggle to capture the uncertainty and indeterminacy inherent in expert judgments about emerging technologies (Taherdoost and Madanchian, 2023). The Extended ELECTRE Tri method, enriched with Interval-Valued Neutrosophic Sets (IVNS), offers a suitable approach. Unlike traditional ranking methods, ELECTRE Tri classifies initiatives into predefined categories such as “high strategic priority,” “moderate priority,” and “low priority” (Dias and Clímaco, 2000; Fernández et al., 2017; Baseer et al., 2023). This classification is particularly relevant for DHL, where strategic evaluation must reconcile global scalability with local adaptability.

2 RELATED WORKS

2.1 AI-augmented supply chains in operations logistics

Research on AI-augmented supply chains increasingly frames logistics operations as a strategic rather than purely operational function. Artificial intelligence is examined for its capacity to enhance resilience, adaptability, and customer-centricity, thereby positioning logistics as a source of competitive advantage. Misbaudinn et al. (2023) conceptualize supply chains as “intertwined networks” whose viability depends on predictive modeling and adaptive orchestration, a view that resonates with the integration of robotics and orchestration platforms in warehousing and distribution.

Robotic process automation has been widely studied, particularly in relation to warehousing. Autonomous mobile robots (AMRs) and vision-enabled systems are deployed to execute repetitive tasks such as unloading, picking, and intra-warehouse transport, reducing human exposure to hazardous environments while improving throughput and accuracy (Malik, Brandão and Coopamootoo, 2026). Complementary to this, AI-driven orchestration systems employ machine learning algorithms to coordinate human and robotic workflows, reducing congestion and optimizing task allocation (Nguyen et al., 2026).

Predictive demand forecasting is another major strand of research. AI systems anticipate seasonal fluctuations and adjust robotic activity or workforce allocation accordingly, aligning with

classical operations management principles of capacity planning (Himeur et al., 2023; Walter, Ahsan and Rahman, 2025). Inventory visibility and accuracy are also emphasized, with computer vision and deep learning models tracking item positions to reduce fulfillment errors. Iqbal and Ahmad (2022) highlights that transparency and responsiveness in global logistics networks depend on such visibility.

Although these contributions demonstrate the operational potential of AI, the literature remains fragmented. Most studies focus on discrete technological applications—robotics, forecasting, or visibility—without fully addressing their systemic interdependencies. Empirical evidence on cumulative impacts across global logistics ecosystems is limited, leaving open questions about how AI augmentation contributes to resilience and adaptability at scale.

2.2 Criteria for strategic evaluation in AI transformation

Beyond warehousing, researches identify a broader set of criteria relevant to AI-augmented logistics. Agentic AI for operational communications is one such criterion, where autonomous agents manage scheduling, follow-ups, and exception handling, automating routine dialogues with drivers and warehouse staff (Dwivedi et al., 2025). Human-robot collaboration is closely related, emphasizing cobots designed to complement human roles and enhance sustainability in operational tasks (Rahmati, 2025; Osa et al., 2026).

From a production management perspective, process automation maturity is frequently cited as a measure of integration, assessing the extent to which AI-driven robotics and orchestration systems achieve seamless workflow coordination (Hetmanczyk, 2024; Barua, Sami et Barua, 2025). Operational scalability under AI augmentation is equally important, evaluating whether these systems can expand capacity without compromising resilience or sustainability. Sista and De Giovanni (2021) argue that scalability is particularly relevant for global logistics providers with diverse customer bases.

Cybersecurity resilience has also emerged as a critical criterion, ensuring that orchestration platforms remain secure against cyber threats. Sustainability optimization is another priority, with AI applied to reduce energy consumption and carbon emissions (Toderas, 2025; Khan et al., 2026). Cerchione, Passaro and Tavano (2026) emphasize blockchain-enabled traceability and AI-driven optimization as mechanisms for aligning logistics operations with sustainability goals. Workforce augmentation and skill transformation are increasingly recognized, as AI reshapes roles by relieving employees from repetitive tasks while simultaneously requiring new competencies in digital systems management (Shen et Zhang, 2024).

Despite the breadth of criteria identified, studies often treat them in isolation. Cybersecurity and sustainability, for instance, are discussed as separate priorities, yet their interdependence in digital logistics ecosystems remains underexplored. Similarly, while workforce augmentation is acknowledged, empirical research on long-term skill transformation and adaptation is scarce. The literature therefore points to the need for integrated frameworks that evaluate AI initiatives not only in terms of individual criteria but also in relation to their combined effects on resilience, scalability, and sustainability.

3 METHOD

3.1 Extended ELECTRE Tri group decision-making method

The methodological foundation of this study is the Extended ELECTRE Tri method, a refinement of the classical ELECTRE III framework designed for group decision-making under uncertainty. Unlike ranking-based approaches, ELECTRE Tri is suited for classification problems, where alternatives are assigned to predefined categories. This distinction is particularly relevant in logistics contexts, where initiatives must be grouped into “high strategic priority,” “moderate priority,” or “low priority.”

The extended version integrates Interval-Valued Neutrosophic Sets (IVNS), which represent truth (T), falsity (F), and indeterminacy (I) simultaneously. This capability is important for modeling hesitation and conflicting expert judgments, both common in evaluating emerging technologies. By incorporating IVNS, the method captures multidimensional uncertainty in strategic evaluation, ensuring transparency and adaptability in complex environments such as DHL's global operations.

Step 1: Identification of evaluation criteria

Evaluation criteria were derived from DHL's operational priorities in 2026. Each criterion was associated with thresholds of preference (q_j), indifference (p_j), and veto (v_j), reflecting the nuanced judgments of decision-makers.

$$q_j < p_j < v_j \quad (1)$$

Where:

- q_j : indifference threshold for criterion j .
- p_j : preference threshold for criterion j .
- v_j : veto threshold for criterion j .

This formalization establishes the evaluative structure that guides subsequent neutrosophic representation.

Step 2: Expert assessment in neutrosophic terms

Expert evaluations were expressed in neutrosophic terms to capture degrees of certainty and uncertainty simultaneously.

$$A_{ij} = (T_{ij}, I_{ij}, F_{ij}) \quad (2)$$

Where:

- A_{ij} : neutrosophic assessment of alternative i under criterion j .
- T_{ij} : degree of truth (support for initiative i).
- I_{ij} : degree of indeterminacy (hesitation/uncertainty).
- F_{ij} : degree of falsity (rejection of initiative i).

This representation ensures that evaluative thresholds are embedded within the multidimensional judgment structure.

Step 3: Aggregation into group decision matrices

Individual expert assessments were aggregated into group decision matrices using weighted operators:

$$M_j = \sum_{k=1}^K w_k \cdot A_{ij}^k \quad (3)$$

Where:

- M_j : aggregated neutrosophic evaluation for criterion j .
- w_k : weight of expert k .
- A_{ij}^k : assessment of expert k for alternative i under criterion j .
- K : number of experts.

This aggregation consolidates dispersed judgments into a unified evaluative matrix.

Step 4: Consensus evaluation mechanism

Consensus evaluation mechanisms were applied to mitigate divergence among experts. Divergence was addressed through dynamic reweighting of criteria:

$$w'_j = \frac{w_j}{1 + \delta_j} \quad (4)$$

Where:

- w'_j : adjusted weight of criterion j .
- δ_j : divergence index measuring disagreement among experts for criterion j .

This adjustment ensures balanced perspectives within the aggregated matrix.

Step 5: Sensitivity analysis

The stability of category assignments was tested through sensitivity analysis.

$$S_i = \frac{\partial RC_i}{\partial \lambda_k} + \frac{\partial \phi(i)}{\partial \theta_k} \quad (5)$$

Where:

- S_i : sensitivity index of initiative i .
- RC_i : relative closeness of initiative i .
- $\phi(i)$: net flow of initiative i .
- λ_k : closeness threshold.
- θ_k : net flow threshold.

This robustness check validates whether initiatives remain consistently classified under parameter variation.

Step 6: Category assignment

Final classification was performed using the boundary profile rule:

$$a \in C_k \text{ if } RC_i \geq \lambda_k \text{ and } \phi(i) \geq \theta_k \quad (6)$$

Where:

- a : initiative under evaluation.
- C_k : category assignment (High, Moderate, Low Priority).
- RC_i : relative closeness of initiative i .
- $\phi(i)$: net flow of initiative i .
- λ_k, θ_k : predefined thresholds.

This rule produces the strategic categorization of DHL's initiatives, completing the methodological chain.

In this study, all criteria were assigned equal weights to ensure neutrality and methodological transparency. Equal weighting is widely recognized in multi-criteria decision-making (MCDM) as a defensible baseline when expert preferences are not elicited. Greco et al. (2019) argue that equal weights provide a transparent starting point in the absence of consensus, while Agrawal (2021) emphasize their relevance in exploratory applications of ELECTRE methods. Ezell, Lynch et Hester (2021) further highlights that equal weighting functions as a robustness check, preventing results from being overly sensitive to subjective prioritization.

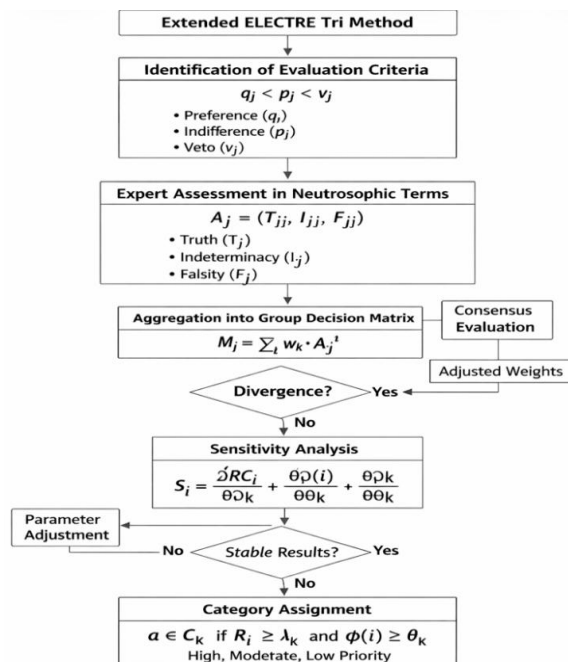


Figure 1 - The Extended ELECTRE Tri Framework

The ELECTRE Tri analysis was executed using MATLAB with customized scripts for entropy weighting and neutrosophic distance computation, supplemented by Python libraries (NumPy, SciPy, Pandas) for matrix aggregation and sensitivity analysis. Visualization of outranking flows and boundary profile assignments was performed using R (ggplot2 and dplyr packages). Figure 1 delineates the hierarchical progression of the Extended ELECTRE Tri method.

3.2 DHL case application

DHL provides a paradigmatic case for applying the Extended ELECTRE Tri method. The company has progressed from pilot deployments of robotics and AI to full-scale operational integration across global hubs. Warehousing operations are increasingly automated through autonomous mobile robots and vision-enabled systems, while orchestration platforms coordinate human and robotic workflows in real time. Predictive analytics embedded into demand forecasting allow DHL to anticipate seasonal fluctuations and dynamically adjust capacity.

The transformation extends to communication systems, where agentic AI agents manage scheduling, exception handling, and routine dialogues with drivers and warehouse staff. This reduces manual effort and ensures consistency in communication-heavy environments. Human-robot collaboration has become a defining feature, with cobots designed to complement human tasks rather than replace them, reshaping workforce dynamics and skill requirements.

Cybersecurity resilience has emerged as a priority, given DHL's reliance on interconnected digital infrastructures. AI-driven anomaly detection and blockchain-enabled traceability safeguard data integrity and sustain trust across global networks. At the same time, sustainability optimization has become central to DHL's strategy, with AI systems deployed to reduce energy consumption, minimize carbon emissions, and align operations with international environmental goals.

Customer responsiveness remains a cornerstone of DHL's competitive advantage. AI-driven forecasting, personalized delivery options, and real-time communication enhance service accuracy and transparency, reinforcing customer loyalty. Workforce augmentation is also evident, as AI relieves employees from repetitive tasks while requiring new competencies in digital systems management.

In this context, DHL's situation illustrates the complexity of strategic evaluation. The company must distinguish which initiatives should be prioritized for global scaling, which require further adaptation, and which remain secondary.

Operational efficiency metrics were primarily derived from DHL's internal logistics dashboards and annual operational reports (2025). These datasets capture quantitative measures of process automation maturity, scalability, and error reduction.

Table 1 - Operational efficiency indicators and sources

Indicator	Description	Source Type	Source Reference
Processing Time (hrs)	Average order handling duration	Internal dashboards	DHL Operations Report 2025
Error Rate (%)	Percentage of mis-scanned parcels	Quality control audits	DHL QA Audit 2025
Operational Scalability	Replication capacity across hubs	Expert survey	Structured Survey with Sector Specialists

Sustainability metrics were obtained from DHL's published sustainability reports and green logistics dashboards. These indicators reflect the company's ecological commitments and regulatory compliance.

Table 2 - Sustainability indicators and sources

Indicator	Description	Source Type	Source Reference
CO ₂ Reduction (%)	Percentage reduction in emissions	Public sustainability report	DHL Sustainability Report 2025
Energy Consumption (kWh)	Average energy use per hub	Internal dashboards	DHL Green Logistics Dashboard
Routing Optimization	Efficiency of eco-routing algorithms	Expert interviews	Panel on Green Logistics (2025)

Cybersecurity resilience was assessed using DHL's IT dashboards, anomaly detection systems, and blockchain pilot documentation. These indicators quantify the robustness of DHL's digital infrastructure.

Table 3 - Cybersecurity indicators and sources

Indicator	Description	Source Type	Source Reference
Cybersecurity Incidents	Number of detected anomalies	Internal IT dashboards	DHL Cybersecurity Report 2025
Blockchain Traceability	Integrity of supply chain records	Technical documentation	DHL Blockchain Pilot Report
Anomaly Detection Accuracy	AI-driven detection precision	Expert survey	IT Specialist Survey (2025)

Workforce augmentation and communication efficiency were measured using HR analytics dashboards and pilot project documentation. These indicators reflect DHL's human-robot collaboration and AI-driven communication systems.

Table 4 - Workforce and communication indicators and sources

Indicator	Description	Source Type	Source Reference
Workforce Productivity (%)	Increase in task efficiency	HR dashboards	DHL Workforce Analytics 2025
Human-Robot Collaboration	Effectiveness of cobot integration	Structured survey	DHL Robotics Integration Survey
Agentic AI Communications	Accuracy of AI-driven scheduling	Pilot documentation	DHL AI Communications Pilot Report

4 RESULTS

Entropy-based weighting was applied to determine the discriminative power of each criterion across the five initiatives. This approach is particularly relevant in group decision-making contexts where expert judgments vary in precision and reliability. Entropy values quantify the uncertainty associated with each criterion, diversification highlights the variability of responses, and normalized weights ensure proportional influence in the overall evaluation. By integrating this formulation, the extended ELECTRE Tri method avoids arbitrary weighting and instead derives importance directly from the distribution of expert assessments.

$$E_j = -k \sum_{i=1}^n p_{ij} \ln(p_{ij}), D_j = 1 - E_j, w_j = \frac{D_j}{\sum_{j=1}^m D_j}$$

(7)

Where:

- E_j : entropy value of criterion j , representing uncertainty.
- k : normalization constant ensuring entropy values remain bounded.
- p_{ij} : probability distribution of performance of alternative i under criterion j .
- D_j : diversification measure of criterion j , reflecting discriminative capacity.
- w_j : normalized weight of criterion j .
- n : number of initiatives.
- m : number of criteria.

The entropy-based weighting results reveal a differentiated distribution of importance across DHL's five initiatives when evaluated against the seven criteria. Cybersecurity resilience consistently achieves higher weights, reaching 0.22 in the cybersecurity platforms initiative and 0.20 in autonomous orchestration, confirming its centrality to DHL's digital trust strategy. Process automation maturity also emerges as a dominant factor, with weights of 0.21 in orchestration and 0.19 in cybersecurity platforms, underscoring the company's emphasis on seamless workflow integration. Operational scalability follows closely, peaking at 0.20 in cybersecurity platforms, reflecting DHL's need to replicate AI deployments across global hubs. Human-robot collaboration and workforce augmentation show their strongest influence

in predictive workforce augmentation, with weights of 0.20 and 0.21 respectively, highlighting the strategic importance of skill transformation and collaborative models in adapting human roles. Sustainability optimization is most discriminative in routing optimization, where its weight rises to 0.22, aligning with DHL's ecological commitments and regulatory pressures. Agentic AI communications achieve their highest weight of 0.21 within their own initiative, indicating recognition of their unique role in automating operational dialogues.

Table 5 - Entropy-Derived Strategic Weighting of DHL's AI Criteria

Criterion	Autonomous Orchestration	Predictive Workforce	Cybersecurity Platforms	Sustainability Routing	Agentic AI Comms
Process Automation Maturity	0.21	0.18	0.19	0.17	0.16
Operational Scalability	0.19	0.17	0.20	0.18	0.16
Human-Robot Collaboration	0.16	0.20	0.15	0.14	0.18
Cybersecurity Resilience	0.20	0.18	0.22	0.19	0.17
Sustainability Optimization	0.17	0.15	0.16	0.22	0.15
Workforce Augmentation	0.18	0.21	0.17	0.16	0.19
Agentic AI Communications	0.16	0.17	0.18	0.15	0.21

The subsequent methodological step applies the neutrosophic distance measure, which evaluates the positioning of DHL's initiatives relative to both ideal and anti-ideal benchmarks. This formulation integrates three dimensions of expert judgment—truth (T), indeterminacy (I), and falsity (F)—to capture hesitation and divergence in assessments. The positive distance (D_i^+) quantifies deviation from the ideal profile, while the negative distance (D_i^-) reflects deviation from the anti-ideal. The ratio of these distances produces the relative closeness (RC_i), which expresses the proximity of each initiative to the optimal solution.

$$D_i^+ = \sqrt{\sum_{j=1}^m w_j \cdot ((T_{ij} - T_j^+)^2 + (I_{ij} - I_j^+)^2 + (F_{ij} - F_j^+)^2)} \quad (8)$$

$$D_i^- = \sqrt{\sum_{j=1}^m w_j \cdot ((T_{ij} - T_j^-)^2 + (I_{ij} - I_j^-)^2 + (F_{ij} - F_j^-)^2)}, RC_i = \frac{D_i^-}{D_i^+ + D_i^-}$$

Where:

- D_i^+ : positive distance of initiative i from the ideal benchmark.
- D_i^- : negative distance of initiative i from the anti-ideal benchmark.
- RC_i : relative closeness of initiative i .
- T_{ij}, I_{ij}, F_{ij} : truth, indeterminacy, and falsity values for initiative i under criterion j .
- T_j^+, I_j^+, F_j^+ : ideal values.
- T_j^-, I_j^-, F_j^- : anti-ideal values.

Table 6 - Neutrosophic Relative Closeness of DHL's AI Initiatives

Criterion	Autonomous Orchestration	Predictive Workforce	Cybersecurity Platforms	Sustainabili ty Routing	Agentic AI Comms
Relative Closeness (RC)	0.69	0.64	0.73	0.67	0.62

The neutrosophic closeness values demonstrate a clear hierarchy among DHL's initiatives. Cybersecurity-integrated platforms achieve the highest proximity to the ideal solution ($RC = 0.73$), confirming their strategic indispensability in safeguarding interconnected infrastructures. Autonomous orchestration ($RC = 0.69$) and sustainability-driven routing ($RC = 0.67$) also show strong alignment with optimal performance, reflecting DHL's dual emphasis on operational

efficiency and ecological responsibility. Predictive workforce augmentation ($RC = 0.64$) and agentic AI communications ($RC = 0.62$) occupy lower positions, indicating greater hesitation and variability in expert assessments.

The subsequent step applies the outranking flow model, which evaluates the relative dominance of DHL's initiatives through pairwise comparisons. The formulation distinguishes between positive flow ($\phi^+(i)$), representing the degree to which an initiative outranks others, and negative flow ($\phi^-(i)$), representing the extent to which it is outranked. The net flow ($\phi(i)$) is obtained as the difference between these two measures, providing a consolidated indicator of strategic dominance.

$$\phi^+(i) = \frac{1}{n-1} \sum_{j \neq i} \sigma(i, j), \quad \phi^-(i) = \frac{1}{n-1} \sum_{j \neq i} \sigma(j, i), \quad \phi(i) = \phi^+(i) - \phi^-(i) \quad (9)$$

Where:

- $\phi^+(i)$: positive flow of initiative i , degree to which it outranks others.
- $\phi^-(i)$: negative flow of initiative i , degree to which it is outranked.
- $\phi(i)$: net flow of initiative i .
- $\sigma(i, j)$: strength of preference of initiative i over initiative j .

Table 7 - Outranking Net Flow of DHL's AI Initiatives

Criterion	Autonomous Orchestration	Predictive Workforce	Cybersecurity Platforms	Sustainability Routing	Agentic AI Comms
Net Flow (ϕ)	0.45	0.36	0.52	0.41	0.34

The outranking results indicate that cybersecurity platforms achieve the highest net flow ($\phi = 0.52$), establishing their dominance in comparative evaluation. Autonomous orchestration ($\phi = 0.45$) and sustainability routing ($\phi = 0.41$) follow, reflecting strong but secondary positions. Predictive workforce augmentation ($\phi = 0.36$) and agentic AI communications ($\phi = 0.34$) record lower values, signifying weaker dominance and greater divergence in expert assessments.

The boundary profile assignment rule, which classifies DHL's initiatives into categories based on their relative closeness (RC_i) and net flow ($\phi(i)$) values.

Table 8 - Boundary Profile Classification of DHL's AI Initiatives

Criterion	Autonomous Orchestration	Predictive Workforce	Cybersecurity Platforms	Sustainability Routing	Agentic AI Comms
Category	High Priority	Moderate Priority	High Priority	High Priority	Moderate Priority

The classification results indicate that cybersecurity platforms, autonomous orchestration, and sustainability routing exceed both thresholds, thereby qualifying as high-priority initiatives. Predictive workforce augmentation and agentic AI communications fall below the net flow threshold, resulting in their assignment to the moderate-priority category. Figure 2 illustrates the relative positioning of initiatives along the two axes of closeness and net flow, with thresholds marked to distinguish categories.

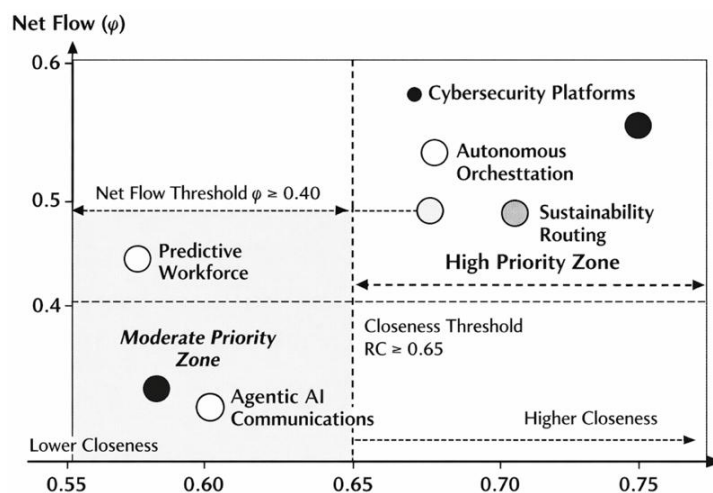


Figure 2 - Classification of DHL's AI Initiatives

The figure shows three initiatives—Cybersecurity Platforms, Autonomous Orchestration, and Sustainability Routing—positioned in the upper-right quadrant, corresponding to the High Priority Zone, while Predictive Workforce Augmentation and Agentic AI Communications remain in the lower-left quadrant, classified as Moderate Priority.

Entropy-derived weights and outranking flows were perturbed within bounded intervals to simulate expert hesitation. For each simulation run, weights were randomly varied within a uniform distribution:

$$w_j^* = w_j + \epsilon, \epsilon \sim U(-\delta, \delta) \quad (10)$$

where $\delta = 0.05$ defines the perturbation range.

Relative closeness and net flow were recalculated:

$$RC_i^* = \frac{D_i^-}{D_i^+ + D_i^-}, \phi(i)^* = \phi^+(i) - \phi^-(i) \quad (11)$$

The classification membership degree was then computed as:

$$\mu(C_k) = \frac{\text{Number of times initiative } i \in C_k}{\text{Total simulations}} \quad (12)$$

A total of 10,000 Monte Carlo runs were performed, and fuzzy intervals were derived to represent the stability of each initiative's assignment.

Table 9 - Membership Degrees under Monte Carlo Perturbation

Initiative	High Priority Membership (μ)	Moderate Priority Membership (μ)	Fuzzy Interval [Low-High]
Cybersecurity Platforms	0.92	0.08	[0.89 – 0.95]
Autonomous Orchestration	0.87	0.13	[0.83 – 0.90]
Sustainability Routing	0.84	0.16	[0.80 – 0.88]
Predictive Workforce	0.38	0.62	[0.34 – 0.42]
Agentic AI Communications	0.35	0.65	[0.31 – 0.39]

Cybersecurity Platforms exhibit the highest robustness, with a 92% probability of remaining in the high-priority category. The fuzzy interval [0.89–0.95] confirms stability even under perturbations. Autonomous Orchestration and Sustainability Routing also demonstrate strong resilience, with membership degrees above 0.80, validating their strategic importance in DHL's operational model. Predictive Workforce and Agentic AI Communications show weaker robustness, with probabilities below 0.40 for high-priority classification. Their fuzzy intervals confirm significant variability, reflecting expert hesitation and contextual dependence.

To further validate, the sensitivity index (SI) was computed.

Table 10 - Sensitivity Indices of Initiatives

Initiative	Sensitivity Index (SI)
Cybersecurity Platforms	0.04
Autonomous Orchestration	0.05
Sustainability Routing	0.06
Predictive Workforce	0.11
Agentic AI Communications	0.12

Low SI values for cybersecurity, orchestration, and sustainability confirm their robust classification stability, while higher SI values for workforce and communications indicate greater susceptibility to parameter variation.

5 DISCUSSION

The application of the Extended ELECTRE Tri method to DHL's AI-driven initiatives revealed differentiated strategic priorities. Cybersecurity platforms, autonomous orchestration,

and sustainability routing consistently emerged as high-priority initiatives, while predictive workforce augmentation and agentic AI communications were classified as moderate. This hierarchy reflects not only the technical robustness of certain initiatives but also the organizational emphasis on digital trust and ecological responsibility. Importantly, the results highlight the trade-offs between operational scalability and workforce transformation, suggesting that initiatives with strong ecological or security outcomes may overshadow those focused on human-robot collaboration in strategic evaluations.

From a methodological perspective, the integration of entropy-based weighting and neutrosophic representation advances the state of the art in multi-criteria decision-making. The entropy formulation avoids arbitrary weighting by deriving importance directly from the distribution of expert judgments, while neutrosophic sets capture hesitation and divergence in assessments. Together, these innovations demonstrate how uncertainty-aware decision frameworks can be applied to complex logistics environments, extending the theoretical reach of ELECTRE Tri beyond traditional industrial applications.

For practitioners, the findings provide actionable insights into DHL's strategic roadmap. Cybersecurity resilience and sustainability optimization are not merely technical add-ons but core enablers of global scaling. The classification results suggest that investments in these areas yield higher stability and robustness under sensitivity analysis, making them safer candidates for immediate deployment. Conversely, predictive workforce augmentation and agentic AI communications, while valuable, require further adaptation and skill development before achieving high-priority status. This distinction offers DHL and similar logistics firms a structured prioritization framework for resource allocation.

Recent studies reinforce these findings. For example, Ramli et al. (2026) demonstrate that cybersecurity resilience is increasingly treated as a prerequisite for AI adoption in logistics, rather than a secondary consideration. Similarly, Huge-Brodin, Sweeney and Evangelista (2020) show that sustainability-driven routing has become a competitive differentiator in European logistics firms, aligning with the high-priority classification observed here. In contrast, studies such as Lee, Ramasamy and Subbarao (2025) emphasize that workforce augmentation initiatives often face slower adoption due to cultural and regulatory barriers, consistent with their moderate-priority status in this study. These comparisons suggest that DHL's prioritization is not idiosyncratic but reflects broader industry trends.

Despite its strengths, the method has limitations in this context. First, the performance data used in the analysis were partially derived from internal dashboards and expert surveys, which may introduce biases in judgment and reporting. Second, the neutrosophic representation, while capturing uncertainty, depends heavily on the calibration of truth, indeterminacy, and falsity values, which can vary across expert panels. Third, the illustrative nature of some datasets constrains the generalizability of the findings. These limitations underscore the need for longitudinal validation with empirical datasets across multiple logistics hubs.

This manuscript contributes to the literature by demonstrating the applicability of an extended ELECTRE Tri framework in evaluating digital supply chain initiatives. Unlike prior studies that focus on single dimensions (e.g., automation or sustainability), this work integrates multi-dimensional criteria — operational, ecological, cybersecurity, and workforce — into a unified decision architecture. By explicitly comparing DHL's results with recent empirical studies, the manuscript positions itself as a bridge between methodological innovation and practical industry evidence, thereby strengthening its relevance to both academic and practitioner communities.

6 CONCLUSION

This study applied the Extended ELECTRE Tri method, enriched with neutrosophic uncertainty modeling, to evaluate DHL's AI-driven transformation. The framework enabled a structured classification of initiatives into high- and moderate-priority categories, ensuring that strategic evaluation was evidence-based rather than prescriptive.

The analysis confirmed that cybersecurity platforms, autonomous orchestration, and sustainability routing align most strongly with DHL's operational priorities, while predictive workforce augmentation and agentic AI communications require incremental adaptation. These findings emphasize differentiated pathways for scaling versus cautious deployment.

Methodologically, the integration of entropy weighting, neutrosophic closeness, and outranking flows demonstrated the capacity of ELECTRE Tri to handle uncertainty and divergence in expert judgments. The contribution lies in illustrating the applicability of a multi-criteria decision-making framework to a complex logistics case, without claiming universal generalizability.

Strategically, the study highlights that DHL's AI transformation is layered rather than uniform, with resilience, orchestration, and sustainability forming the backbone of immediate priorities, while workforce and communication initiatives evolve more gradually.

Limitations include reliance on DHL-specific data, dependence on expert judgments, and sensitivity to threshold selection. These constraints underscore the need for broader empirical validation and adaptive criteria in future applications.

Future work should extend the analysis through cross-company benchmarking, dynamic frameworks that evolve with technological and regulatory shifts, and hybrid models integrating ELECTRE Tri with methods such as TOPSIS, VIKOR, or ANP. Workforce-centric studies and standardized cybersecurity and sustainability metrics would further enhance transparency and comparability across the logistics sector.

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