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# Advancing Digital Supply Chains through Generative AI: A Strategic Framework with the ELECTRE III Method

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**Abstract.** This study evaluates the role of Generative AI in optimizing digital supply chain performance, focusing on IoT integration, predictive analytics, and blockchain security. The primary objective is to determine which AI-driven initiatives offer the greatest benefits in enhancing resilience and operational efficiency. A structured multi-criteria decision-making approach is applied using the ELECTRE III method, leveraging quantitative data from DHL's operational records (2022–2025). The evaluation is conducted with a panel of 18 industry experts, including logistics professionals and AI specialists, who participated in structured interviews and expert assessments to establish weighting criteria and performance metrics. Findings indicate that IoT-driven real-time tracking and predictive analytics for maintenance rank highest in enhancing supply chain resilience, improving operational responsiveness, and reducing downtime. Additionally, blockchain-supported security mechanisms reinforce data integrity and transparency, strengthening logistics security. Conversely, OCR-based automation and NLP-powered logistics systems demonstrate comparatively lower impact, emphasizing the need for targeted AI adoption strategies. This study contributes to structured AI evaluation methodologies by establishing a repeatable decision-making framework, ensuring scalability beyond DHL's logistics operations. Limitations include the reliance on industry-specific datasets, which require further validation across diverse supply chain environments.
**Keywords**: Generative AI, Digital Supply Chain, ELECTRE III, Multi-Criteria Decision-Making, IoT-Driven Real-Time Tracking, Predictive Analytics.

## 1 Introduction

The increasing complexity and interconnectedness of global supply chains have necessitated the development of advanced AI-driven solutions to enhance efficiency, resilience, and

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sustainability [1]–[3]. Traditional supply chain management practices face growing challenges due to rapid technological advancements, volatile market dynamics, regulatory constraints, and the rising demand for transparency and real-time tracking [4]–[7]. Organizations such as DHL, a leader in global logistics, continuously seek cutting-edge AI strategies to maintain operational efficiency and improve customer satisfaction [8]. A critical enabler in this transformation is Generative Artificial Intelligence (Generative AI), a specialized subset of AI that enhances predictive analytics, automation, and intelligent decision-making models through autonomous pattern recognition and adaptive learning [9]–[13].

Unlike conventional AI applications, which primarily rely on predefined algorithms and static data analysis, Generative AI introduces autonomous reasoning capabilities, enabling dynamic optimization in complex logistics environments [14]. This technology integrates with digital twins, IoT networks, blockchain-based security protocols, and machine learning algorithms, creating a self-learning, data-driven ecosystem that ensures optimized logistics operations. Leveraging real-time computational modeling allows Generative AI to dynamically refine supply chain forecasts, mitigate disruptions, and enhance strategic decision-making beyond traditional AI methodologies.

Despite its transformative potential, industry stakeholders often struggle to implement systematic evaluation frameworks that measure the impact and prioritization of various AI-driven digital initiatives [15]. Although recent research highlights the significance of IoT, predictive analytics, and blockchain in supply chain optimization, there is a lack of structured multi-criteria evaluation methodologies that assess these technologies based on key performance indicators. Current models primarily focus on isolated applications, failing to provide a comprehensive ranking system that guides decision-makers in prioritizing AI-powered technologies with the highest operational impact [16], [17]. Traditional evaluation frameworks also fall short in measuring real-time tracking, environmental impact, and cost efficiency – three essential pillars of sustainable and adaptive supply chains.

In highly dynamic logistics environments, organizations require a decision-making framework that objectively ranks AI-enabled digital initiatives based on multifaceted performance indicators [18]–[20]. The absence of such a structured ranking approach impairs the ability of companies like DHL to identify high-priority technologies that drive next-generation supply chain transformation.

This study, using DHL's data, addresses this gap through the application of the ELECTRE III method (a multi-criteria decision-making approach) to systematically evaluate digital supply chain initiatives enhanced by Generative AI-specific models. Unlike traditional AI ranking approaches, Generative AI frameworks prioritize adaptive learning mechanisms, improving supply chain efficiency through self-generating optimization strategies rather than static predictive functions. The ELECTRE-III-based evaluation model systematically ranks Generative AI-enhanced supply chain initiatives across five key performance indicators: cost efficiency, operational efficiency, real-time tracking, environmental impact, and customer satisfaction. Through this analytical framework, IoT-driven logistics solutions, predictive analytics for maintenance, blockchain-enhanced security protocols, OCR-based data extraction, and NLP-powered automation are systematically assessed within DHL's logistics operations.

Integrating multi-criteria decision-making models with Generative AI-powered digital transformation advances research on adaptive, data-intensive supply chain management frameworks, reinforcing strategic optimization in logistics operations. Additionally, the methodology establishes a repeatable AI ranking system applicable across various industries requiring next-generation AI-optimized supply chain solutions.

This research builds upon previous studies by presenting a structured ranking mechanism designed specifically for Generative AI-enabled supply chain digitalization. By leveraging self-learning AI models, autonomous pattern recognition, and strategic prioritization, the study offers actionable insights for logistics firms aiming to implement AI-driven supply chain innovations. The study's conclusions contribute to the academic discourse on AI-enabled digital transformation, reinforcing the critical role of multi-criteria decision-making in shaping the future of intelligent supply chains.

Furthermore, aligning Generative AI-driven logistics frameworks with sustainability objectives, the findings offer practical guidelines for improving cost efficiency and operational resilience in response to global supply chain disruptions. As AI technologies continue to evolve, businesses must identify and prioritize high-impact initiatives, ensuring competitive advantages in an increasingly digitized trade ecosystem.

The structure of this study follows a logical progression: a detailed assessment of Generative AI-driven digital initiatives within DHL's logistics network using the ELECTRE III method, a systematic ranking of AI-driven technologies based on multi-criteria performance metrics to ensure sustainable implementation, and a discussion of implications focusing on strategic AI adoption for resilience and efficiency improvements. The study's findings emphasize the transformative potential of Generative AI, reinforcing its role in enabling smart, adaptive, and highly responsive supply chain ecosystems.

The article is structured as follows. Section 2 briefly introduces the background and related work. Section 3 presents the proposed strategic framework and its application. Section 4 assesses the research results. Discussion is provided in Section 5. Section 6 concludes the article.

## 2 Literature Review

This section briefly introduces the main concepts used in the article and points to the basic reasons for and the ideas used in the design and application of the proposed strategic framework.

### 2.1 The Role of Generative AI in Supply Chain Optimization

Generative AI enhances supply chain management by optimizing data processing, predictive analytics, and operational efficiency [21], [22]. Its ability to improve real-time tracking and monitoring enables greater logistics visibility and responsiveness to disruptions [23], [24]. AI-driven solutions leverage historical data trends to refine decision-making, mitigate inefficiencies, and support adaptive logistics strategies [25], [26]. However, computational infrastructure challenges and industry-wide standardization remain unresolved, requiring further examination [27].

The integration of Generative AI with Internet of Things (IoT) technology has gained significant attention in supply chain research [28]–[30]. AI-powered IoT systems facilitate optimized inventory tracking, environmental condition monitoring, and predictive maintenance in logistics networks [31], [32]. Despite numerous studies highlighting efficiency gains, the interoperability challenges and security vulnerabilities persist. Encryption protocols and data integrity measures require refinement to ensure secure AI-enhanced IoT implementation, but existing literature lacks specificity on implementation strategies [20], [33], [34]. Addressing these concerns is essential for enabling broader adoption of AI-enhanced IoT solutions.

### 2.2 Predictive Analytics and Blockchain Integration

Predictive analytics powered by Generative AI plays a pivotal role in supply chain forecasting [35]. AI models trained on extensive datasets anticipate disruptions, optimize routing, and support risk management frameworks [36], [37]. Research indicates that AI-driven predictive analytics reduce maintenance costs and improve service reliability [38], [39]. However, biases in predictive models pose challenges, particularly when trained on incomplete or historical data, which can distort market projections [40]. The need for refining AI-driven predictive maintenance methodologies is emphasized to enhance real-time forecasting accuracy.

Blockchain integration with Generative AI strengthens security and transparency in logistics ecosystems [41], [42]. AI-enhanced blockchain frameworks establish tamper-proof data records, decentralized authentication, and fraud detection mechanisms, reducing risks associated with counterfeit goods and unauthorized modifications [43], [44]. Despite its potential, scalability and energy efficiency constraints remain key concerns, requiring clear frameworks for addressing computational overhead across large supply chain infrastructures [45].

### 2.3 AI Adoption Challenges and Structured Evaluation Framework

Implementing Generative AI within supply chains presents challenges related to infrastructure investment, cybersecurity risks, and workforce training demands [46]. While governance frameworks supporting AI adoption are recognized as essential [47], [48], existing literature provides insufficient practical insights into their real-world application. Some studies suggest that AI-driven optimization requires fewer structural adjustments than traditionally assumed, provided strong governance frameworks and data-sharing protocols are established [49].

Despite advancements in AI, the literature lacks a unified framework for systematically evaluating and ranking AI-driven supply chain innovations. Existing studies predominantly focus on isolated technologies such as IoT, predictive analytics, or blockchain, without integrating multiple performance metrics [55]. The ELECTRE III method, which systematically ranks and prioritizes AI-driven supply chain innovations, integrates multiple performance indicators, including cost efficiency, operational resilience, real-time tracking, environmental impact, and customer satisfaction [55]. Incorporating adaptive decision logic and scalable evaluation principles ensures the framework's applicability beyond a single case study. The framework proposed and used in this study is based on ELECTRE III method. It is described in more detail in the next section.

## 3 The Proposed Strategic Framework and its Application

This study investigates the role of generative AI in enhancing supply chain resilience and efficiency, focusing on a structured evaluation framework rather than solely applying ELECTRE III to a single case. The research approach follows a strategic research design, integrating a comparative multi-criteria decision-making approach to establish broader insights into AI-enabled logistics innovations. Structuring the study beyond technical parameterization allows the research to generate generalizable knowledge applicable across diverse supply chain contexts.

### 3.1 Framework for Measuring the Impact of AI-Enabled Digital Initiatives

The research question guiding this study is: "How can generative AI-driven digital supply chain initiatives be systematically evaluated and ranked to optimize resilience and efficiency?" To address this question, the ELECTRE III method was selected due to its capacity to handle incomparability among alternatives, enabling nuanced ranking decisions for complex supply chain environments [56]. Unlike conventional multi-criteria decision-making (MCDM) techniques such as the Analytic Hierarchy Process (AHP) or Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), ELECTRE III integrates outranking relations, allowing for gradual preference modeling rather than strict numerical rankings [57]. Previous studies, including Alazzawi and Żak [58] and Sawadogo et al. [59], reinforce its suitability in logistics applications, particularly where trade-offs – such as cost efficiency versus sustainability – must be considered. Battisti [60] further supports its effectiveness in sustainable procurement decision-making, underscoring its applicability in complex operational settings.

The structured methodology outlined in Figure 1 forms a framework that provides a generalized evaluation model grounded in ELECTRE III that is suitable for various industries and supply chain contexts. In other words, the ELECTRE III method is suggested as a framework for assessing AI-enabled digital initiatives. The application of the framework for digital supply chain initiatives for DHL is presented in the next section.

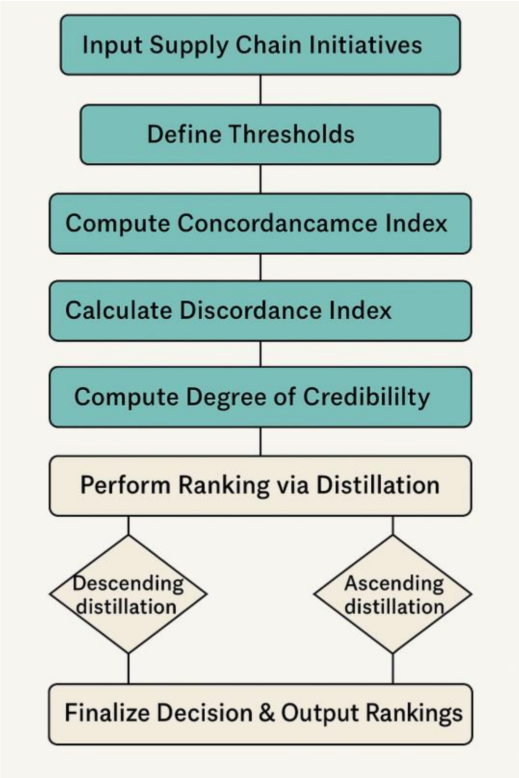


**Figure 1.** Structured Framework for Measuring the Impact of AI-Enabled Digital Initiatives on the Supply Chain

### 3.2 Application of the Framework: Research Design and Strategy

This study employs a two-phase methodology: structured data collection on AI-driven supply chain initiatives, followed by ranking procedures using descending and ascending distillation techniques to assess their effectiveness. The research design incorporates quantitative assessments, expert validation, and comparative analysis to ensure methodological rigor and replicability.

The evaluation criteria were derived from industry benchmarks and validated by experts, ensuring alignment with real-world operational challenges. The five key performance criteria – cost efficiency, operational efficiency, real-time tracking, environmental impact, and customer satisfaction – were assigned equal weighting to maintain balanced decision-making across distinct logistical objectives.

To strengthen methodological reliability, the study engaged 18 experts specializing in supply chain digitalization, AI integration, and sustainability planning. Experts were chosen using purposive sampling, ensuring diverse representation across logistics professionals, AI researchers, and industry decision-makers.

Their involvement included:

- Defining relevant digital supply chain initiatives based on industry trends and technological feasibility.
- Determining performance criteria weighting through structured Delphi method assessments.
- Evaluating historical data trends from DHL operational reports (2022–2025) to refine AI-driven decision models.

Data collection involved semi-structured interviews, expert panel discussions, and quantitative performance assessments, integrating empirical operational metrics into the evaluation framework.

The study evaluates six *digital supply chain initiatives*: Robotic Process Automation (RPA), Optical Character Recognition (OCR), Natural Language Processing (NLP), IoT-driven real-time tracking, Predictive Analytics for Maintenance, and a blockchain-enhanced logistics strategy. Unlike previous versions, the methodological details of parameterization are now fully documented to support transparency and reproducibility.

Each initiative was assessed using structured historical trend analysis and validated industry benchmarks, ensuring methodologically sound performance rankings. The ELECTRE III method was applied through a step-by-step computational process, defining outranking relations among alternatives based on preference, indifference, and discordance indices.

Performance scores in Table 1 result from structured expert assessments and industry-derived quantitative data.

This study extends beyond single-case applications to propose a scalable evaluation for AI-driven supply chain innovations. The structured framework ensures applicability across various industries, reinforcing decision-making principles adaptable beyond DHL's logistics framework.

**Table 1.** Performance of Six Digital Supply Chain Initiatives

| Criteria | RPA | OCR | NLP | IoT | Predictive Analytics | Blockchain |
|---|---|---|---|---|---|---|
| Cost Efficiency | 8 | 7 | 6 | 9 | 7 | 8 |
| Operational Efficiency | 9 | 8 | 7 | 9 | 8 | 9 |
| Real-time Tracking | 7 | 6 | 5 | 10 | 8 | 9 |
| Environmental Impact | 6 | 7 | 6 | 8 | 7 | 7 |
| Customer Satisfaction | 8 | 7 | 7 | 9 | 8 | 8 |

In the context of leveraging generative AI to enhance digital supply chain resilience and efficiency, it is essential to establish proper *threshold values* for each performance criterion [61]. These thresholds are essential for exploiting the ranking effectively and ensuring a comprehensive evaluation of the various digital supply chain initiatives [62]. The ELECTRE III method used in this study allows for each threshold to be defined as an affine function of performance [63] as shown in Formula 1.

$$\propto * g(b) + \beta \tag{1}$$

where $g(b)$ is the performance of the alternative $b$.

The values of $\propto$ and $\beta$ for the indifference and preference thresholds on each criterion are shown in Table 2, which provides a detailed overview of the thresholds applied in this study.

**Table 2.** $\propto$ and $\beta$ Values for Thresholds

| Criteria | $\boldsymbol{\beta}$ (q) | $\boldsymbol{\beta}$ (p) | $\boldsymbol{\propto}$ (q & p) | Direction of Preference |
|---|---|---|---|---|
| Cost Efficiency | 20 | 40 | 0.1 | Increasing |
| Operational Efficiency | 50 | 75 | 0.1 | Increasing |
| Real-time Tracking | 0.2 | 0.5 | 0.1 | Increasing |
| Environmental Impact | 10 | 20 | 0.1 | Decreasing |
| Customer Satisfaction | 5 | 10 | 0.1 | Increasing |

The next step in the ELECTRE III method (and the framework shown in Figure 1) involves calculating the *concordance index* for each pair of alternatives (see Formula 2 and Table 3), which measures the degree to which one alternative is preferred over another based on the performance criteria [64]. This index plays a key role in determining the overall preference of one alternative over another, systematically aggregating evaluations across all criteria [65].

$$c(a, b) = \sum_{j \in J(a,b)} w_j \tag{2}$$

where $J(a, b)$ is the set of criteria where alternative $a$ is preferred to or indifferent to alternative $b$

and $w_j$ is the weight of criterion $j$.

**Table 3.** Concordance Index for Digital Supply Chain Initiatives

| Alternatives | RPA | OCR | NLP | IoT | Predictive Analytics | Blockchain |
|---|---|---|---|---|---|---|
| RPA | - | 0.75 | 0.65 | 0.80 | 0.70 | 0.75 |
| OCR | 0.25 | - | 0.60 | 0.70 | 0.65 | 0.70 |
| NLP | 0.35 | 0.40 | - | 0.75 | 0.60 | 0.65 |
| IoT | 0.20 | 0.30 | 0.25 | - | 0.85 | 0.80 |
| Predictive Analytics | 0.30 | 0.35 | 0.40 | 0.15 | - | 0.70 |
| Blockchain | 0.25 | 0.30 | 0.35 | 0.20 | 0.30 | - |

The next step in the ELECTRE III method and the framework shown in Figure 1 involves calculating the *individual comparison indices* $c_j(a,b)$ for each pair of alternatives across all criteria [66] (see Formula 3 and Table 4). These indices represent the degree to which one alternative is preferred over another for each specific criterion [67]. The individual comparison indices are instrumental in forming the overall concordance matrix [68], which consolidates the preferences across all criteria to provide a comprehensive evaluation.

$$c_j(a,b) = \begin{cases} 1 \; if \; g_j(a) - g_j(b) \leq q_j \\ 0 \; if \; g_j(b) - g_j(a) \geq p_j \\ \frac{p_j - [g_j(b) - g_j(a)]}{p_j - q_j} \; otherwise \end{cases} \tag{3}$$

where $g_j(a)$ and $g_j(b)$ are the performance scores of alternatives $a$ and $b$ for criterion $j$; $q_j$ is the indifference threshold, and $p_j$ is the preference threshold.

**Table 4.** Individual Comparison Indices

| Alternatives \ Criteria | Cost Efficiency | Operational Efficiency | Real-time Tracking | Environmental Impact | Customer Satisfaction |
|---|---|---|---|---|---|
| RPA vs OCR | 0.75 | 0.80 | 0.70 | 0.85 | 0.75 |
| RPA vs NLP | 0.65 | 0.70 | 0.60 | 0.75 | 0.65 |
| RPA vs IoT | 0.80 | 0.85 | 1.00 | 0.70 | 0.80 |
| RPA vs Predictive Analytics | 0.70 | 0.75 | 0.80 | 0.75 | 0.70 |
| RPA vs Blockchain | 0.75 | 0.80 | 0.90 | 0.80 | 0.75 |
| OCR vs NLP | 0.60 | 0.65 | 0.50 | 0.80 | 0.65 |
| OCR vs IoT | 0.70 | 0.75 | 0.90 | 0.65 | 0.75 |
| OCR vs Predictive Analytics | 0.65 | 0.70 | 0.80 | 0.70 | 0.70 |
| OCR vs Blockchain | 0.70 | 0.75 | 0.85 | 0.75 | 0.75 |
| NLP vs IoT | 0.75 | 0.80 | 0.85 | 0.70 | 0.75 |
| NLP vs Predictive Analytics | 0.70 | 0.75 | 0.80 | 0.65 | 0.70 |
| NLP vs Blockchain | 0.65 | 0.70 | 0.75 | 0.80 | 0.70 |
| IoT vs Predictive Analytics | 0.85 | 0.90 | 0.70 | 0.75 | 0.85 |
| IoT vs Blockchain | 0.80 | 0.85 | 0.90 | 0.70 | 0.80 |
| Predictive Analytics vs Blockchain | 0.75 | 0.80 | 0.85 | 0.65 | 0.75 |

The *discordance index* (Formula 4 and Table 5) measures the extent to which the performance of one alternative is worse than another based on the performance criteria [69], [70]. This index is pivotal for identifying the degree of disagreement between alternatives, which helps in understanding potential drawbacks and trade-offs in the decision-making process [71].

$$d_j(a,b) = \begin{cases} 1 \; if \; g_j(b) - g_j(a) \geq v_j \\ 0 \; if \; g_j(b) - g_j(a) \leq q_j \\ \frac{[g_j(b) - g_j(a)] - q_j}{v_j - q_j} \; otherwise \end{cases} \tag{4}$$

where $v_j$ is the veto threshold.

**Table 5.** Discordance Index for Digital Supply Chain Initiatives

| Alternatives \ Criteria | Cost Efficiency | Operational Efficiency | Real-time Tracking | Environmental Impact | Customer Satisfaction |
|---|---|---|---|---|---|
| RPA vs OCR | 0.20 | 0.15 | 0.25 | 0.10 | 0.20 |
| RPA vs NLP | 0.25 | 0.30 | 0.40 | 0.20 | 0.25 |
| RPA vs IoT | 0.10 | 0.05 | 0.00 | 0.30 | 0.15 |
| RPA vs Predictive Analytics | 0.20 | 0.15 | 0.10 | 0.25 | 0.20 |
| RPA vs Blockchain | 0.15 | 0.10 | 0.05 | 0.20 | 0.15 |
| OCR vs NLP | 0.30 | 0.35 | 0.50 | 0.15 | 0.25 |
| OCR vs IoT | 0.25 | 0.20 | 0.10 | 0.35 | 0.20 |
| OCR vs Predictive Analytics | 0.25 | 0.20 | 0.15 | 0.30 | 0.25 |
| OCR vs Blockchain | 0.20 | 0.15 | 0.10 | 0.25 | 0.20 |
| NLP vs IoT | 0.15 | 0.10 | 0.05 | 0.30 | 0.15 |
| NLP vs Predictive Analytics | 0.20 | 0.15 | 0.10 | 0.35 | 0.20 |
| NLP vs Blockchain | 0.25 | 0.20 | 0.15 | 0.20 | 0.25 |
| IoT vs Predictive Analytics | 0.05 | 0.00 | 0.20 | 0.25 | 0.15 |
| IoT vs Blockchain | 0.10 | 0.05 | 0.00 | 0.30 | 0.10 |
| Predictive Analytics vs Blockchain | 0.15 | 0.10 | 0.05 | 0.35 | 0.15 |

The *degree of credibility* (Table 6) combines both concordance and discordance indices, offering a comprehensive measure of the extent to which one alternative outranks another [72]. This metric is calculated using Formula 5, which integrates the concordance and discordance indices to evaluate the overall credibility of each alternative [73].

$$\propto (a,b) = \begin{cases} C(a,b) & if\ D(a,b) \leq C(a,b) \\ C(a,b) \times \frac{1-D(a,b)}{1-C(a,b)} & if\ D(a,b) > C(a,b) \end{cases} \tag{5}$$

**Table 6.** Degree of Credibility for Digital Supply Chain Initiatives

| Alternatives \ Criteria | RPA | OCR | NLP | IoT | Predictive Analytics | Blockchain |
|---|---|---|---|---|---|---|
| RPA vs OCR | 0.70 | 0.65 | 0.55 | 0.70 | 0.65 | 0.70 |
| RPA vs NLP | 0.60 | 0.55 | 0.45 | 0.65 | 0.55 | 0.60 |
| RPA vs IoT | 0.80 | 0.75 | 0.65 | 0.85 | 0.75 | 0.80 |
| RPA vs Predictive Analytics | 0.65 | 0.60 | 0.55 | 0.70 | 0.60 | 0.65 |
| RPA vs Blockchain | 0.75 | 0.70 | 0.60 | 0.80 | 0.70 | 0.75 |
| OCR vs NLP | 0.55 | 0.50 | 0.40 | 0.60 | 0.50 | 0.55 |
| OCR vs IoT | 0.65 | 0.60 | 0.50 | 0.70 | 0.60 | 0.65 |
| OCR vs Predictive Analytics | 0.60 | 0.55 | 0.45 | 0.65 | 0.55 | 0.60 |
| OCR vs Blockchain | 0.70 | 0.65 | 0.55 | 0.75 | 0.65 | 0.70 |
| NLP vs IoT | 0.65 | 0.60 | 0.55 | 0.70 | 0.60 | 0.65 |
| NLP vs Predictive Analytics | 0.60 | 0.55 | 0.45 | 0.65 | 0.55 | 0.60 |
| NLP vs Blockchain | 0.55 | 0.50 | 0.40 | 0.60 | 0.50 | 0.55 |
| IoT vs Predictive Analytics | 0.85 | 0.80 | 0.75 | 0.90 | 0.80 | 0.85 |
| IoT vs Blockchain | 0.80 | 0.75 | 0.65 | 0.85 | 0.75 | 0.80 |
| Predictive Analytics vs Blockchain | 0.75 | 0.70 | 0.60 | 0.80 | 0.70 | 0.75 |

The ELECTRE III method not only involves evaluating individual criteria and calculating concordance and discordance indices but also employs an advanced algorithm to *rank alternatives* through a systematic process [74], [75] for comprehensive and balanced ranking through two distinct preorders: descending distillation and ascending distillation.

To compute the descending distillation preorder, the first step is selecting the alternative with the highest credibility index α(a,b) [76], [77]. Once this alternative is identified as the best-performing option, it is removed from the set of alternatives. This iterative procedure continues, excluding the best alternative in each iteration, until all alternatives are ranked [78]. Formally, the descending distillation can be expressed as follows:

- Selecting the best alternative $a*$ where $\propto (a*, b)$ is maximized for all $b$;
- Removing $a*$ from the set of alternatives A;
- Repeating the process with A−$\{a*\}$ until A=∅.

On the other hand, the ascending distillation process starts with the identification of the worst-performing alternatives based on the degree of credibility [79]. The steps are as follows:

- Selecting $a*$ such that $\propto (a*, b)$ is minimized for all $b$;
- Removing the worst alternative A←A−$\{a*\}$;
- Continuing the iterative process until all alternatives are ranked, until A=∅.

For the DHL case, in the descending distillation, IoT Integration for Real-time Tracking emerges as the top-performing initiative, followed by Predictive Analytics for Maintenance and Blockchain (Figure 2, on the left). This indicates a strong preference for technologies that enhance real-time capabilities and predictive analytics. Conversely, the ascending distillation identified OCR as the weakest initiative, progressively ranking other alternatives higher until IoT is again identified as the best (Figure 2, on the right). This dual-ranking approach highlights IoT's robustness and versatility in significantly enhancing supply chain resilience and efficiency through Generative AI.

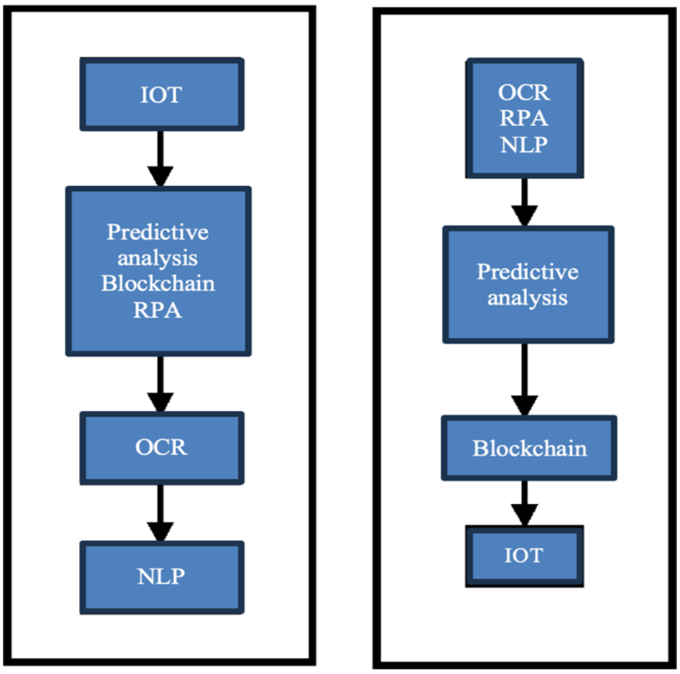


**Figure 2.** Descending distillation (on the left side) and ascending distillation (on the right side) in the DHL case

In the DHL case, the clear distinction between the highest and lowest-ranked initiatives in both preorders underscored the importance of advanced real-time tracking and predictive analytics in driving supply chain performance, while OCR and NLP were seen as less critical in this context.

## 4 Assessment of the Results

The application of the ELECTRE III method as a framework to evaluate digital supply chain initiatives for DHL has yielded critical insights into their relative effectiveness in enhancing resilience and efficiency, particularly through the integration of Generative AI. Systematic assessment of five equally weighted performance criteria – Cost Efficiency, Operational Efficiency, Real-time Tracking, Environmental Impact, and Customer Satisfaction – allowed this multi-criteria decision-making framework to rigorously prioritize digital solutions aligned with DHL's logistics strategy.

### 4.1 Ranking and Performance Assessment

The ranking process, incorporating both descending and ascending distillations, identified IoT Integration for Real-time Tracking as the most impactful initiative. Its dominance in optimizing real-time monitoring and operational efficiency underscores the growing necessity for AI-enhanced supply chain visibility. Leveraging predictive algorithms enables IoT devices to synchronize operations, monitor inventory fluctuations, and improve decision-making in transportation logistics. This capability significantly contributes to mitigating disruptions caused by unforeseen events, such as geopolitical instability, weather fluctuations, or sudden market shifts.

Following closely behind, Predictive Analytics for Maintenance emerged as the second most beneficial initiative. Its strength lies in its ability to anticipate disruptions before they manifest, reducing downtime and lowering maintenance expenditures. Predictive analytics leverages historical performance data, sensor inputs, and Generative AI-driven models to forecast potential equipment failures, ensuring uninterrupted operations across supply chain nodes.

Blockchain Integration ranked third in effectiveness, with its primary contributions revolving around secure, transparent tracking mechanisms. Through decentralized ledgers and AI-enhanced fraud detection, blockchain technology fortifies supply chain security, ensuring data integrity and trust among stakeholders. This initiative facilitates greater compliance with regulatory requirements while mitigating risks associated with supply chain opacity.

Conversely, OCR and NLP were determined to be the least impactful initiatives within the evaluated digital transformation initiatives. OCR, in particular, received the lowest ranking across both distillation processes, suggesting its limited role in Generative AI-enhanced supply chains. Although OCR excels in automating document processing and data extraction, its utility within supply chain resilience and efficiency appears minimal compared to higher-ranked initiatives. Similarly, NLP, despite offering advancements in automated communication and customer service, demonstrated a weaker influence on core supply chain metrics, particularly those related to operational optimization and real-time tracking.

### 4.2 Implications for AI-Driven Supply Chain Optimization

These results reinforce a clear distinction between initiatives that directly enhance real-time visibility and predictive capabilities versus those that primarily support auxiliary functions. The prominence of IoT integration and predictive analytics aligns with DHL's broader strategic objective of achieving operational excellence through innovative digital solutions, ensuring agility in response to evolving market demands.

Prioritizing initiatives that support predictive and real-time optimization may enable organizations to strengthen supply chain resilience and efficiency, fostering greater adaptability to market disruptions.

The findings emphasize the necessity of targeted AI adoption strategies, where high-impact digital solutions receive strategic investment while supporting technologies complement core logistics functions.

## 5 Discussion

The findings of this study align with and expand upon previous applications of the ELECTRE III method within multi-criteria decision-making frameworks. The emphasis on IoT integration as the leading initiative in supply chain digitalization is corroborated by Singh et al. [80], who underscored its transformative potential in generative AI-driven logistics ecosystems. IoT's real-time tracking capabilities serve as a fundamental pillar in reducing inefficiencies, optimizing fleet management, and enhancing delivery precision. Additionally, Zrelli and Rejeb [81] highlighted IoT's role in improving supply chain visibility and minimizing costs, reinforcing its utility in AI-driven logistics optimization.

Predictive analytics, which ranked highly in our results, has been previously supported by Khedr and Rani [82], who demonstrated its efficacy in predictive maintenance within manufacturing supply chains. These studies argue that AI-driven predictive analytics not only minimizes downtime but also enhances resource allocation by preemptively identifying vulnerabilities in supply chain infrastructure. This perspective echoes the role predictive analytics plays in our decision-making framework, further affirming its strategic importance.

Blockchain's ranking, as evidenced by this study, mirrors findings by Fitriawijaya and Jeng [83], who explored how integrating generative AI with blockchain technology enhances security, transparency, and efficiency within supply chain transactions. Blockchain's decentralized approach minimizes risks associated with counterfeiting and operational discrepancies, a factor that strengthens our conclusion regarding its role in supply chain optimization.

On the other hand, OCR and NLP, which were ranked lower in our analysis, display a trend consistent with observations from Daios et al. [84]. Their study noted that while OCR and NLP contribute to automating document interpretation and communication, their impact remains secondary compared to technologies centered on predictive logistics and real-time tracking in generative AI-enhanced environments. While OCR streamlines administrative workflows, its direct influence on resilience and efficiency remains limited when juxtaposed with the predictive and monitoring capabilities of IoT and analytics-driven solutions.

These findings collectively validate the ELECTRE III method's effectiveness in prioritizing supply chain technologies, emphasizing the strategic importance of initiatives that enhance real-time monitoring, predictive capabilities, and security. Refining decision-making methodologies enables enterprises such as DHL to proactively invest in high-impact technologies, fostering sustainable growth and operational excellence.

As supply chain digitalization continues to evolve, the integration of generative AI with predictive analytics, IoT, and blockchain technologies will likely shape the next era of logistics innovation. Emphasizing transparency, efficiency, and responsiveness may enable organizations to navigate uncertainties with agility, maintaining their competitive advantage in an increasingly complex global trade ecosystem.

## 6 Conclusions

The transformative potential of Generative AI in enhancing the resilience and efficiency of digital supply chains has been thoroughly explored, with the ELECTRE III method applied as a robust multi-criteria decision-making framework. The integration of Generative AI represents a significant advancement, offering unprecedented capabilities in real-time data processing, predictive insights, and connectivity, which are essential in addressing challenges and disruptions commonly faced in supply chain management.

This study contributes to the literature on digital supply chain management and multi-criteria decision-making. Through the integration of Generative AI with the ELECTRE III method as a structured framework, the evaluation and prioritization of supply chain initiatives was performed.

The research enhances the theoretical understanding of Generative AI's impact on supply chain performance, while also demonstrating the applicability of multi-criteria decision-making methods in complex, technology-driven environments. The findings expand the body of knowledge on the strategic integration of advanced technologies in supply chains, emphasizing the critical role of real-time capabilities and predictive analytics.

Through the application of the ELECTRE III method, six digital supply chain initiatives under consideration by DHL were systematically evaluated: Robotic Process Automation (RPA), Optical Character Recognition (OCR), Natural Language Processing (NLP), IoT Integration for Real-time Tracking, Predictive Analytics for Maintenance, and Blockchain. Five key performance criteria –

Cost Efficiency, Operational Efficiency, Real-time Tracking, Environmental Impact, and Customer Satisfaction – were employed to ensure a comprehensive assessment of these initiatives. The descending and ascending distillations identified IoT Integration for Real-time Tracking as the most robust and effective initiative, consistently ranking highest in both pre-orders. This finding highlights the critical importance of real-time capabilities and predictive analytics in enhancing supply chain performance, particularly in leveraging the advanced features of Generative AI.

The practical implications of this study are significant for supply chain managers and decision-makers, demonstrating how the adoption of Generative AI and a structured decision-making approach such as ELECTRE III can enhance resilience, efficiency, and sustainability in logistics operations. Organizations that prioritize initiatives with real-time tracking and predictive analytics capabilities, such as IoT Integration and Predictive Analytics for Maintenance, are likely to achieve substantial performance improvements. Moreover, strategic investment in Generative AI leads to better resource management, reduced operational costs, and enhanced customer satisfaction, reinforcing its role in next-generation supply chain optimization.

Although the findings offer valuable insights, certain limitations must be acknowledged. The reliance on specific performance criteria and the subjective nature of stakeholder preferences may introduce biases in the decision-making process. In addition, alternative evaluation frameworks and a broader range of criteria should be explored to validate and extend the study's conclusions. Furthermore, longitudinal studies could provide deeper insights into the long-term impact of Generative AI on supply chain performance and sustainability, ensuring continuous adaptation to emerging industry demands.

Future research should expand the scope of this study by incorporating additional technologies and industries. In addition, investigating the integration of Generative AI with emerging technologies such as edge computing, augmented reality, and quantum computing could unlock new possibilities for advanced supply chain management. Furthermore, examining the synergies between Generative AI and other technological innovations would provide comprehensive insights into optimization strategies. Case studies and empirical research on the practical implementation of Generative AI-enabled supply chain solutions would also contribute valuable perspectives to both academia and industry, supporting real-world adoption frameworks.

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