

INTEGRATING GENERATIVE AI INTO INTERMODAL ROUTE OPTIMIZATION – 3PL APPLICATION AND THEORETICAL INSIGHTS

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Purpose: The aim of this article is to analyze the potential applications of generative artificial intelligence (Gen-AI), specifically the GPT-4o and Gemini Advanced models, in optimizing intermodal transport routes. Particular emphasis is placed on the use of these tools by 3PL logistics operators to enhance route planning efficiency, reduce the number of transshipments, and minimize transport distance.

Design/methodology/approach: The study employs an experimental approach, utilizing Gen-AI models to plan intermodal routes based on real-world data concerning terminals and transport connections in Europe. The models were trained on literature related to both route optimization and previous applications of generative AI. The experiment included an analysis of two route variants: minimizing the number of transshipments and minimizing the total travel distance. The results of both models were compared, and mutual validation was conducted.

Findings: The results indicate that GPT-4o was more effective in accounting for real-world intermodal terminal connections, providing operationally viable routes. In contrast, Gemini Advanced occasionally suggested connections that lacked correspondence with the actual dataset, limiting their practical applicability.

Research limitations/implications: The main limitations of the study stem from the lack of dynamic operational data, such as real-time changes in transport schedules or terminal closures. Additionally, Gen-AI models operate as "black boxes", making it difficult to fully interpret the decision-making process.

Originality/value: This study introduces a new perspective on research into intermodal transport route optimization, demonstrating the potential for synergistic use of Gen-AI models. The application of large language models in logistics can support 3PL operators in making better transport decisions.

Keywords: 3PL, generative AI, GPT, Gemini, route optimization, intermodal transportation.

Category of the paper: Research paper.

1. Introduction

Intermodal transport logistics, based on the integration of various modes of transportation—such as rail, road, air, and sea—plays a key role in global supply chains (Bhattacharya et al., 2014). Route optimization in this context is essential for reducing transit time, minimizing costs (Sahin et al., 2014), and increasing supply chain flexibility, sustainability, and resilience (Goodarzi et al., 2024). Due to the complexity of transportation networks, route planning must consider multiple factors, including schedules, infrastructure constraints, transport availability, and dynamic disruptions such as weather conditions, regulatory changes, or geopolitical threats (Pedersen, 2005; Wang et al., 2018). Another significant challenge is the diversity of transport modes, which differ in terms of costs, delivery time, infrastructure requirements, and operational flexibility (Li et al., 2015). This necessitates precise synchronization between different supply chain links, as well as effective management of transshipment points, where cargo must be efficiently transferred between transport modes. Additionally, regulatory and administrative complexity in intermodal transport presents a major challenge (Eftestøl et al., 2014). Different countries and regions enforce varying regulations regarding freight transport, customs procedures, weight restrictions, and documentation requirements, which can lead to delays and additional operational costs.

There is increasing recognition that 3PL providers play a crucial role in intermodal systems, particularly in planning and coordinating such activities (Zografos, Regan, 2004; Xu et al., 2015). By employing advanced route optimization strategies in both single- and multimodal transport environments, 3PL providers not only improve operational efficiency and delivery reliability but also support sustainability goals by reducing fuel consumption and CO₂ emissions (Li et al., 2024). Given the growing complexity of intermodal logistics and the challenges associated with route optimization, modern AI-based technologies are becoming increasingly significant (Prakash et al., 2024). In particular, generative AI, represented by models such as GPT (Generative Pre-trained Transformer) and Gemini, has the potential to transform decision-making processes in logistics (Kmiecik, 2023; Fosso Wamba et al., 2024). The potential of generative AI in 3PL logistics is undoubtedly vast; however, fully leveraging it requires further research and integration with existing transport management systems (TMS) and analytical platforms. Research increasingly explores the applications of broadly understood Gen-AI or specific models within it. This article also contributes to this trend. It will present the theoretical framework and examples of generative AI applications in intermodal route optimization, as well as discuss the challenges associated with implementing this technology. The originality of this study lies in the synergistic use of two advanced generative AI models (GPT-4o and Gemini Advanced) for intermodal route optimization, an approach that has not yet been systematically explored in the literature. Unlike previous research that typically focuses on either heuristic optimization algorithms or single-model AI applications, this paper

introduces a dual-model framework where both LLMs generate, evaluate, and refine each other's solutions. This collaborative mechanism enhances reliability and mitigates the limitations of single-model approaches, thereby offering new theoretical insights and practical implications for 3PL operators. Accordingly, the article focuses on addressing the following research question:

RQ.1: What are the theoretical frameworks and practical applications of Gen-AI in route planning for intermodal transport by 3PL providers?

The article consists of the following sections:

- Literature Review – This section presents key methods for route planning in intermodal transport and previous research on the application of generative AI in logistics.
- Methodology – This section describes the research steps, AI models used, and input data applied in the experiment, including information on terminals and intermodal connections.
- Results – This section presents the experimental results, showcasing the generated transport routes and an analysis of their effectiveness and accuracy concerning real-world connections.
- Discussion – This section analyzes the implications of the findings, highlighting the strengths and weaknesses of the applied methods and discussing the impact of generative AI on intermodal logistics theory.
- Conclusions – This section summarizes the main research findings, emphasizing the potential of AI in transport route optimization and the challenges that need to be overcome in future implementations.

By outlining the research question and the article's structure, it sets the foundation for a comprehensive exploration of how large language models can contribute to both theoretical insights and practical advancements in route planning.

2. Literature review

2.1. Key Route Planning Methods in Intermodal Transportation

Paper Intermodal transport plays a crucial role in global supply chains by ensuring cost efficiency, reducing CO₂ emissions, and improving the management of logistical resources. One of the most significant challenges in intermodal transport planning is route optimization, which must consider multiple criteria such as delivery time, transportation costs, node capacity, and operational uncertainty. This subsection provides an overview of algorithms used in intermodal route planning, highlighting their advantages and limitations. Intermodal route planning can be modeled as a mathematical optimization problem, where transportation costs,

emissions, and delivery times are minimized. Chang (2008) proposed an approach based on Lagrangian relaxation and subgradient optimization, focusing on the shortest path problem with time windows and the knapsack problem. A similar approach is employed by Hosseini and Al Khaled (2021), who use mixed-integer programming (MIP) and linear relaxation methods to optimize multi-commodity flows. Bi-level Mixed Integer Nonlinear Programming (MINLP) enables the optimization of train schedules and the selection of transshipment stations, though its application is limited due to high computational requirements (Chen et al., 2022). In a similar vein, Wang et al. (2018) designed a model based on memetic algorithms, incorporating demand uncertainty and time constraints.

Traditional optimization methods are increasingly being replaced by metaheuristics, which allow near-optimal solutions to be found within a reasonable computational time. Li et al. (2023) utilized a genetic algorithm (GA) and heuristics based on the balance of competitive government subsidies in intermodal hub location selection. The ant colony optimization (ACO) algorithm has been applied in research by Sawadogo et al. (2012), where shortest path optimization accounted for both cost and CO₂ emissions. Similarly, Zhao et al. (2019) proposed a hybrid Co-Simulation Optimization (COSMO) approach that integrates traffic prediction with heuristic optimization. Dynamic optimization is also the subject of research by Wang et al. (2023), who applied an improved quantum genetic algorithm (IQGA) for intermodal routing under the constraints of bounded rationality among travelers. Likewise, Rosyida et al. (2020) designed a model based on simulated annealing (SA) and K-means clustering for historical data analysis. Operational uncertainty and random disruptions pose key challenges in intermodal route planning. Anghinolfi et al. (2011) developed a hybrid ACO algorithm combined with integer programming to dynamically adjust routes. Meanwhile, Peng et al. (2021) applied fuzzy optimization and NSGA-II to model uncertainty in multimodal transport. Sun et al. (2022) also addressed uncertainty management, employing chance-constrained programming and interval methods for intermodal transport optimization. Similarly, Xu et al. (2024) proposed a hybrid GA-PSO algorithm for dynamically adjusting routes under crisis conditions.

The main algorithms used for route planning are described in Table 1. Additionally, the table highlights key barriers identified in the reviewed studies related to the methodologies adopted in the respective articles.

Table 1.

Main limitations and weaknesses of chosen route planning methods

Source	Routing Algorithms Considered	Main Limitations and Weaknesses
Chang, 2008	Lagrange Relaxation, Subgradient Optimization, Shortest Path Problem with Time Windows (SPPTW), Bounded Knapsack Problem	NP-hard model, heuristics do not guarantee global optimum, limited real-world testing
Hosseini, Al Khaled, 2021	Mixed Integer Programming (MIP), Linear Relaxation, Multi-Commodity Flow Problem	Uncertainty in congestion modeling, limited empirical data, lack of dynamic adaptation

Cont. table 1.

Chen et al., 2022	Bi-level Mixed Integer Nonlinear Programming (MINLP), Grid-Based Adaptive Artificial Bee Colony (GBA-ABC), NSGA-II	Computational complexity of bi-level optimization, limited real-world tests
Wang et al., 2018	Memetic Algorithm (MA), Integer Programming (IP), Shift and Exchange Heuristic	Incomplete consideration of market variables, limited validation on real-world data
Li et al., 2023	MIP, Intelligent Location Algorithm Based on Government Subsidies (ILAGS), Genetic Algorithm (GA)	Lack of analysis on dynamic subsidy changes, deterministic model
Sawadogo et al., 2012	Multiobjective Ant Colony Optimization (MOSPACO), Pareto Sorting	High number of iterations, time-consuming, lack of testing on large instances
Vale, Ribeiro, 2018)	Multi-Objective Evolutionary Algorithm (MOEA), NSGA-II, Multi-Objective Ant Colony Optimization (MOACO)	Does not consider dynamic traffic conditions, static approach
Zhao et al., 2019	Co-Simulation Optimization (COSMO), Column Generation, Dynamic User Equilibrium (DUE)	Model requires high computational power, limited congestion impact analysis
Wang et al., 2023	Improved Quantum Genetic Algorithm (IQGA), Non-Dominated Sorting Genetic Algorithm-II (NSGA-II), Penalty Function Method	Computational complexity, lack of real-world testing
Rosyida et al., 2020	Genetic Algorithm (GA), Simulated Annealing (SA), K-Means Clustering	No adaptation to dynamic disruptions, limited model scalability
Wang et al., 2023)	Improved Quantum Genetic Algorithm (IQGA), Non-dominated Sorting Genetic Algorithm-II (NSGA-II)	No real-world analysis, computational complexity
Anghinolfi et al., 2011	Integer Programming (IP), Ant Colony Optimization (ACO), Hybrid ACO (HACO)	High heuristic complexity, limited efficiency in large-scale problems
Wang et al., 2020	Fuzzy Mixed Integer Linear Programming (FMILP), Interval-Based Optimization	Incomplete consideration of dynamic transport cost changes
Peng et al., 2021	Fuzzy Multi-Objective Optimization, NSGA-II, Tournament Selection	Limited empirical testing, lack of real-world validation
Sun et al., 2022	Fuzzy Multi-Objective Optimization, Chance-Constrained Programming (FCCP), Interactive Fuzzy Programming	Uncertainty in input data may affect optimization results
Ru, 2024	Tabu Search (TS), Graph Traversal Algorithm, P-Median	Does not consider real-time dynamic changes
Sirikijpanichkul et al., 2007	Agent-Based Modelling (ABM), Integer Programming (IP), Simulated Annealing	Does not consider dynamic infrastructure changes
Sun et al., 2014	Column Generation, Labeling Algorithm, Benders Decomposition	Limited scalability, no testing in dynamic conditions
Shao et al., 2022	NSGA-III, Dominance-Based Rough Set Approach (DRSA), Monte Carlo Simulation	Incomplete consideration of customer preferences, no analysis of dynamic cost changes
Han et al., 2022	Fuzzy C-Means Clustering (FCM), MILP, Genetic Algorithm (GA)	No adaptation to dynamic transport conditions
Xu et al., 2024	Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Hybrid GA-PSO	No full validation on real-world operational data
Zografos, Madas, 2003	Lexicographic Ordering, Dynamic Routing, Complete Enumeration	No dynamic adaptation to real-world traffic conditions

Source: own work.

A review of the literature indicates that route optimization in intermodal transport is associated with several limitations stemming from both the nature of the problem and the algorithms used. The main challenges include computational complexity, lack of dynamic adaptation, difficulties in modeling uncertainty, limited integration with user preferences, and insufficient validation of algorithms in real-world operational conditions. Many optimization problems are NP-hard, meaning that classical deterministic algorithms may be insufficient for large problem instances, and methods such as Mixed Integer Programming (MIP) or bi-level optimization require significant computational resources. As a result, their application in dynamic operational conditions is highly constrained. Another challenge is that most existing approaches rely on static models, which do not account for real-world changes such as operational disruptions, delays, or fluctuations in transport availability. Uncertainty modeling remains problematic as well—while some methods use fuzzy models or probabilistic approaches, challenges persist regarding prediction accuracy and adaptability to real conditions. A further key limitation is the lack of integration with user preferences. Route optimization often focuses on minimizing costs and delivery times, overlooking subjective customer expectations such as delivery flexibility, reliability, or environmental impact. Lastly, many algorithms are tested on synthetic datasets or theoretical models, which do not guarantee effectiveness in real-world transport operations.

Given these limitations, an important question arises: Could the development of large language models (LLMs) and generative artificial intelligence (Gen-AI) help solve these problems? Potential applications of these technologies include improved analysis of historical data and prediction of operational conditions, which could enhance uncertainty modeling and forecasting of dynamic changes. LLMs could also support heuristic and metaheuristic optimization, generating alternative routing strategies adapted to variable conditions. Another promising application area is real-time disruption management—by analyzing current operational data, LLMs could enable dynamic route adjustments in response to changing conditions.

2.2. The Role of Gen-AI in Route Planning for Intermodal Transport

Generative artificial intelligence (Gen-AI) is one of the breakthrough technologies that has recently gained widespread popularity. In the context of route planning in intermodal transport, unlike traditional route optimization methods that primarily rely on deterministic algorithms and heuristic rules, generative AI can leverage machine learning models to dynamically adjust routes based on changing operational conditions. This subsection presents key applications of generative AI in areas related to route planning and optimization. Several studies have attempted to link Gen-AI with route planning. The most prominent applications include:

- Generative Adversarial Networks (GANs) – Used for traffic prediction and the analysis of alternative routing scenarios in dynamic conditions (Ye et al., 2024; Zhang et al., 2024).
- Deep Reinforcement Learning (DRL) – Applied to dynamic route optimization, particularly in fleet management and electric vehicle route planning (Zhang et al., 2024; Adelusola, 2024).
- Digital Twins – Simulations of real-world transport conditions that allow testing different route variants in intermodal models before deployment (Mohamed, 2024; Asimiyu, 2024).
- Variational Autoencoders (VAEs) – Used for dimensionality reduction of transport data and travel pattern analysis in intermodal networks (Zhang et al., 2024).
- Transformers in Generative AI – Leveraging language models to analyze textual descriptions of transport conditions and provide routing recommendations (Kleinová, Straka, 2024).

Each of these technologies enables more precise and flexible decision-making regarding routes, which is crucial in intermodal transport, where variable transport conditions, multiple transport modes, and dynamic scheduling changes must be considered. Intermodal transport undoubtedly requires coordination among multiple transport modes, such as rail, maritime, air, and road transport. Generative AI enables real-time dynamic route planning, utilizing the techniques presented in Table 2.

Table 2.
Gen-AI in the context of route planning

Area	Brief description	Source
Traffic intensity forecasting and identification of optimal transport corridors	Generative AI algorithms can analyze historical data as well as real-time information from IoT systems, GPS sensors, and city cameras to predict traffic intensity and determine the best routes for different modes of transport	Ye et al. (2024), Zhang et al. (2024)
Route adaptation based on weather and infrastructure conditions	Intermodal transport is particularly vulnerable to disruptions caused by weather conditions, infrastructure failures, or labor strikes. DRL models and digital twins enable dynamic route modifications based on current operational conditions	Mohammed (2024), Aimiyyu (2024)
Transshipment management and transfer time optimization	A key challenge in intermodal transport is minimizing transshipment time between transport modes. Generative AI, leveraging reinforcement learning algorithms, can dynamically allocate resources and predict optimal moments for cargo transfers, reducing operational bottleneck	Adelusola (2024), Zhang et al. (2024)

Source: own work.

One of the key trends in intermodal transport management is the minimization of the carbon footprint and the increase in energy efficiency. According to the author, generative AI can support this process in a manner similar to "traditional" AI. Such applications could include optimizing routes with a focus on CO₂ emissions reduction. AI models can analyze various transport options (e.g., choosing rail over trucks) and recommend those variants that minimize

fuel consumption and CO₂ emissions while maintaining delivery efficiency (Zhang et al., 2024; Kleinová, Straka, 2024). In road transport, AI can take into account the availability of charging stations, forecast network congestion, and estimate charging times, enabling route optimization for EV fleets (Zhang et al., 2024). Generative AI can also model regulatory scenarios, such as carbon taxes, environmental fees, or low-emission zone restrictions, and recommend route adjustment strategies to comply with these requirements (Asimiyu, 2024). Despite significant progress in the application of generative AI for route optimization in intermodal transport, there are still major research challenges that require further exploration. Most AI systems used in logistics function as "black boxes". There is a lack of research on AI models that can explain their routing decisions transparently to logistics managers (Adelusola, 2024).

Currently, there are no coherent models integrating generative AI with blockchain to enhance the transparency and security of decision-making processes in intermodal transport (Mohamed, 2024). It is essential to develop AI models that combine the predictive power of generative neural networks with the computational efficiency of classical methods, such as heuristic and metaheuristic algorithms (Kleinová, Straka, 2024). Unlike classical heuristic approaches, generative AI enables planners to incorporate context-sensitive insights—such as weather disruptions or infrastructure constraints—into real-time route adjustments. This contributes not only to operational efficiency, but also to environmental objectives like emission reduction. However, significant research challenges remain concerning the transparency of decision-making in intermodal transport. Recognizing these challenges, the author has undertaken an attempt to test the capabilities of selected Gen-AI tools in the context of intermodal transport planning optimization.

3. Methods

3.1. Main Research Steps

The study presented in this article focused on testing selected LLM models (GPT-4o and Gemini Advanced) in the development of an optimization tool for route planning in intermodal transport from the perspective of a third-party logistics (3PL) company. Figure 1 illustrates the general workflow corresponding to the research process conducted in this study.

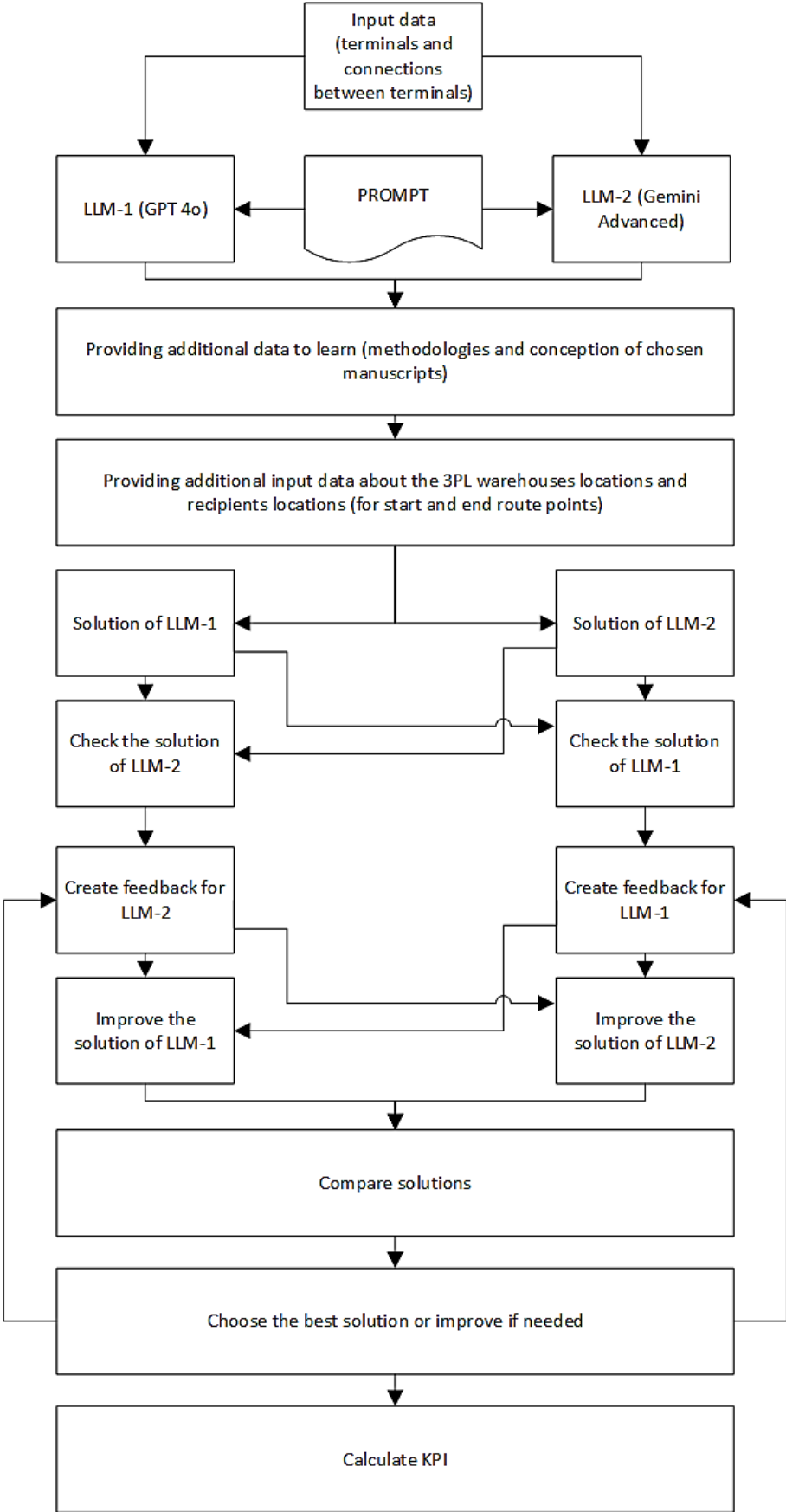


Figure 1. Research workflow.
Source: own work.

The workflow presented in the block diagram describes the route planning process in intermodal transport using two generative artificial intelligence models (LLMs): GPT-4o (LLM-1) and Gemini Advanced (LLM-2). A key aspect of this approach is the synergistic interaction between both models, which mutually support and refine each other's solutions. This complementary use of two LLMs is rarely found in the scientific literature and represents an innovative approach to route optimization in logistics. The process begins with the collection of input data, including information on terminals and connections between them, which serves as the basis for further analysis. Based on this data, a prompt is formulated, initiating the solution generation process by both LLMs. Next, both models receive additional data in the form of scientific articles on methodologies and concepts related to intermodal transport route planning. This knowledge enrichment enhances their understanding of the problem and improves the quality of generated solutions.

In the subsequent step, additional input data is provided, including the locations of 3PL warehouses and recipient locations, defining the starting and ending points of transport routes. Based on this, both models generate their initial route optimization solutions. Notably, each model then evaluates the solution generated by the other model, identifying potential errors, gaps, or areas requiring improvement. Based on the mutual evaluation, a feedback set is created, which is used to refine the initial solutions. Both GPT-4o and Gemini Advanced incorporate adjustments to their solutions based on the received feedback. Upon completing this stage, both models provide updated versions of their proposals, which are then compared in terms of effectiveness and efficiency. A comparative analysis is conducted to select the best solution. If neither solution fully meets expectations, the iterative process is repeated to further improve the results.

The final stage involves the calculation of key performance indicators (KPIs), which enable a quantitative assessment of the efficiency of the selected route, considering criteria such as cost-effectiveness, delivery time, and environmental impact. The novelty of this approach lies in the synergistic use of two advanced LLMs, which not only generate their own solutions but also support each other through analysis and evaluation of each other's outputs. This collaborative AI model application in route optimization represents a significant contribution to research on the application of artificial intelligence in logistics and intermodal transport.

3.2. Data Collection

The input data used in the analysis of the research problem consisted of two types of data:

- Data related to the locational specifications and connections between intermodal terminals.
- Data on best practices in intermodal transport route optimization and the use of generative AI tools for solutions indirectly related to the topic explored in the article.

The experiment involved planning intermodal transport from Warsaw (Poland) to Madrid (Spain) under two scenarios: A scenario that minimizes the number of transshipments (i.e., reducing the number of intermediate terminals) and a scenario that results in the shortest possible route. The data related to locational specifications (Table 3) and terminal connections (Table 4) also reflected real-world distribution and intermodal terminal connections across Europe.

Table 2.

Sample of input data – terminals locations

Terminal_full	City	Terminal_short	Latitude	Longitude
Terminal A	City A	TA	59,4462329	24,7612584
Terminal B	City A	TB	59,4435257	24,7656147
Terminal C	City B	TC	57,7814568	26,0550403
...

Source: own work.

The dataset contains information on 291 intermodal transport terminals. It includes the full terminal name along with the city name, facilitating location identification in conjunction with route data. Additionally, the dataset provides the city where the terminal is located, a shortened terminal name for quick identification and the geographical coordinates of each terminal, enabling precise location mapping and distance calculations between terminals for route optimization.

Table 3.

Sample of input data – terminals connections

operator	service name	trip number	Terminal end
Operator A	ABC	1	Terminal A
Operator A	ABC	1	Terminal B
Operator B	XYZ	1	Terminal A
...

Source: own work.

The dataset contains information on existing transport connections operated by various providers. It includes 1,176 records with data that identify the name of the transport operator managing a given route, the name of the transport service, allowing identification of specific routes operated by each provider, the course number, distinguishing individual trips within the same service and the name of the stop or terminal, indicating stopping points for each journey. This data enables the analysis of how different routes connect terminals across various cities, which is essential for optimizing freight flow in intermodal transport. However, the dataset may not include all intermodal connections, as access to complete databases is limited, and only selected data segments were available for analysis. The input data on best practices involved importing scientific articles into the LLM models, covering topics such as intermodal transport route optimization and the application of generative AI solutions to similar problems (Table 4). All article sources had been previously referenced in the literature review section of this article.

Table 4.
Literature sources for additional LLM training

Sources used for additional LLM training about intermodal routes optimization	
Sources about intermodal route optimization	Sources about gen-AI usage in similar problems
Chang (2008), Hosseini, Al Khaled (2021), Chen et al. (2022), Wang et al. (2018), Li et al. (2023), Sawadogo et al. (2012), Vale, Ribeiro (2018), Zhao et al. (2019), Wang et al. (2023), Rosyida et al. (2020), Wang et al. (2023), Anghinolfi et al. (2011), Wang et al. (2020), Peng et al. (2021), Sun et al. (2022), Ru (2024), Sirikijpanichkul et al. (2007), Sun et al. (2014), Shao et al. (2022), Han et al. (2022), Xu et al. (2024), Zografos, Madas (2003)	Ye et al. (2024), Zhang et al. (2024), Zhang et al. (2024), Adelusola (2024), Mohamed (2024), Asimiyu (2024), Zhang et al. (2024), Kleinová, Straka (2024), Ye et al. (2024), Zhang et al. (2024), Mohammed (2024), Aimiyu (2024), Adelusola (2024), Zhang et al. (2024)

Source: own work.

The research process involved analyzing data related to 3PL operator activities, terminal locations, and connections between them, as well as implementing best practices in route optimization and the application of generative AI. The datasets provided information on real-world routes and terminals across Europe, enabling an accurate representation of operational conditions. The next section will briefly describe the Gemini and GPT models and present the justification for selecting these technologies for the study.

3.3. GPT and Gemini models

Generative AI models, particularly large language models (LLMs) such as GPT (Generative Pre-trained Transformer) and Gemini, represent a breakthrough in artificial intelligence (Baytak, 2024). These models are designed to process and generate human-like text based on extensive training on diverse datasets. Their architecture enables them to perform a wide range of tasks, from language translation and content generation to complex decision-making and optimization tasks.

GPT, developed by OpenAI, is an autoregressive language model that leverages deep learning to generate human-like text. It is built on a Transformer architecture, allowing it to effectively handle long-term dependencies and contextual understanding. The version used in this study, GPT-4o, has been fine-tuned on a vast corpus of textual data, enabling it to produce coherent and contextually relevant outputs across various domains (Deng, Lin, 2022). Key operational characteristics of GPT-4o, identified through its documented specifications and behavior during the experiment, include:

- **Contextual Understanding:** Excels at comprehending complex queries and generating detailed responses.
- **Flexibility:** Can be adapted to specific tasks, such as route optimization, by incorporating domain-specific data.
- **Iterative Learning:** Improves its performance based on feedback, which is crucial for optimization tasks requiring gradual improvements.

Gemini, developed by Google DeepMind, is another advanced LLM designed to handle complex problem-solving tasks (McIntosh et al., 2023). Unlike GPT, Gemini possesses multimodal capabilities, allowing it to process and integrate data from various sources, including text, numerical data, and geospatial information. Key features of Gemini Advanced (according to information provided by the model itself):

- **Multimodal Integration:** Ability to synthesize information from different data formats, enhancing decision-making processes.
- **Advanced Reasoning:** Excels at logical reasoning, identifying patterns and correlations that may be overlooked by traditional models.
- **Synergistic Capabilities:** Complements GPT by providing alternative perspectives and verifying the robustness of generated solutions.

Most studies compare Gemini and GPT in a competitive manner, analyzing their respective strengths and weaknesses (Qi et al., 2023; Gunay et al., 2024; Rane et al., 2024). The novelty of this research lies in the synergistic use of GPT-4o and Gemini Advanced. Instead of relying on a single model, this approach leverages the strengths of both LLMs to achieve better optimization results. Additionally, this method may help mitigate the issue of LLM hallucinations, which remains a significant challenge in AI applications across various domains (Ji et al., 2023; Marting et al., 2023; Wei et al., 2023). By having the two models cross-validate each other's outputs, this collaborative mechanism enhances reliability, ensuring that the final routing decisions are well-thought-out, comprehensive, and tailored to dynamic intermodal transport conditions.

The methodology designed for this study integrates both quantitative data on intermodal terminals and connections with qualitative insights from the literature. By applying two complementary generative AI models in a synergistic framework, the research ensures a robust comparison of alternative route planning strategies. This methodological approach establishes a solid foundation for the subsequent presentation and evaluation of results in Chapter 4.

4. Results

4.1. First Routes Creation

The first part of the results focuses on demonstrating how the prompts were structured and how the selected LLMs responded to them. The initial steps involved loading additional information into the LLMs, including best practices for intermodal route planning and best practices for using generative AI for similar purposes. The first queries to the LLMs were aimed at reinforcing their knowledge based on the provided sources (Table 5). Due to limitations on uploading multiple files simultaneously, the files were divided into smaller batches and uploaded incrementally into the LLMs.

Table 5.*Prompts – additional knowledge*

<p>Prompt 1: I am posting here a collection of scientific articles related to road optimization in intermodal transport. I would like you to analyze them and collect best practices from them (also taking into account the limitations). I don't want you to write them down for me, but I want you to learn and remember them. I'll tell you what happens next later. I will send you these files in few parts.</p> <p>Prompt 2: Now I am sending you articles that show the use of generative AI in related matters, such as route planning in intermodal transport. I want you to learn from them as well, I'll tell you what to do next later. I will send them in few parts.</p>	
GPT 4o (LLM 1)	Gemini Advanced (LLM 2)
<p>Answer 1: I analyzed all submitted articles on route optimization in intermodal transport and identified best practices and limitations of the methods used. I will remember this information so that I can use it later according to your further instructions. Let me know what to do next.</p> <p>Answer 2: I analyzed the provided articles on route optimization in intermodal transport and the use of generative AI in related issues such as transport route planning. I acquired knowledge about best practices, limitations and possibilities of using AI in the context of intermodal route optimization and related fields of logistics.</p>	<p>Answer 1: Okay, I've analyzed these articles and collected the best practices in optimizing routes in intermodal transport. I've also taken into account the limitations. I'm ready for further instructions.</p> <p>Answer 2: I have analyzed the articles you provided on the use of generative AI in tasks related to intermodal transport route planning. I have learned about various applications of generative AI in this domain.</p>

Source: own work.

The next phase involved providing batch input data related to the locations and connections of intermodal terminals in Europe (Table 6).

Table 6.*Prompts – terminal locations and connections*

<p>Prompt 1: now I will send you a database related to the location of intermodal terminals in Europe. Do you understand her? [<i>here was sent the data shown previously in table 2</i>].</p> <p>Prompt 2: and now I will send the second part of the database related to connections between different terminals, do you understand it? [<i>here was sent the data shown previously in table 3</i>]</p>	
GPT 4o (LLM 1)	Gemini Advanced (LLM 2)
<p>Answer 1: Yes, I understand the database. It contains the locations of intermodal terminals in Europe, with the following columns: (...) If you want, I can perform further analysis, e.g. visualization of terminals on a map, density analysis or connections with intermodal routes. Let me know what to do next.</p> <p>Answer 2: Yes, I understand the second part of the database. It contains information about connections between intermodal terminals and consists of the following columns: (...) If you want, I can analyze this data in terms of the connection network, most frequently served routes, visualization of connections on a map or other analytical aspects. Let me know what to do next.</p>	<p>Answer 1: Yes, I understand the database you sent. It contains information about intermodal terminals in Europe, including their names, cities, and coordinates. I'm ready to use this data for further analysis or tasks you might have in mind. Is there anything specific you would like me to do with this database now that I have processed it?</p> <p>Answer 2: Yes, I understand the second database you sent. It contains information about connections between different terminals, including the operator, service name, trip number, and city stop. I can use this information to identify the relationships between the terminals in the first database.</p>

Source: own work.

In the next phase of collaboration with the LLMs, they were tasked with solving the problem outlined in the article—planning an intermodal transport route. The prompt used was as follows:

Prompt: *I want to plan intermodal transport from Warsaw (Poland) to Madrid (Spain). Based on the best practices related to the articles I have sent, your own knowledge and these two databases, plan the route of this transport (i.e. the starting terminal, intermediate terminals (if any) and the final terminal) in two variants: the first variant is to minimize the distance and the second variant is to minimize the number of reloadings (intermediate terminals) on the route.*

Subsequently, GPT-4o generated a response, while Gemini Advanced first asked an additional question regarding the explanation of two types of data from the database. After the user provided clarification, Gemini Advanced also generated its response (Table 7).

Table 7.

First routes generated by LLMs

Routes generated by	
GPT 4o (LLM 1)	Gemini Advanced (LLM 2)
<p>In the condition of shortest route:</p> <ol style="list-style-type: none"> 1. Warsaw (Poland) 2. Gądkki (Poland) 3. Schwarzhede (Germany) 4. Duisburg (Germany) 5. Bayonne (France) 6. Irun (Spain) 7. Madrid (Spain) <p>In the condition of reloading points minimization:</p> <ol style="list-style-type: none"> 1. Warsaw (Poland) 2. Gądkki (Poland) 3. Schwarzhede (Germany) 4. Duisburg (Germany) 5. Bayonne (France) 6. Irun (Spain) 7. Madrid (Spain) 	<p>In the condition of shortest route:</p> <ol style="list-style-type: none"> 1. Warsaw (Poland) 2. Poznań (Poland) 3. Berlin (Germany) 4. Paris (France) 5. Madrid (Spain) <p>In the condition of reloading points minimization:</p> <ol style="list-style-type: none"> 1. Warsaw (Poland) 2. Berlin (Germany) 3. Paris (France) 4. Madrid (Spain)

Source: own work.

In the next step, the LLMs were asked to provide the logic (along with a step-by-step Python script) that would reflect the "thought process" of the models (Table 8).

Table 8.*First routes generated by LLMs*

Prompt: Now give me the logic behind your reasoning. Preferably in Python script or another language you feel comfortable with	
GPT 4o (LLM 1)	Gemini Advanced (LLM 2)
<p>The script builds a graph of intermodal terminals based on the provided databases and calculates optimal routes according to two criteria: minimizing the distance and minimizing the number of reloadings.</p> <p>[script]</p> <p>This script performs the following steps:</p> <ul style="list-style-type: none"> Loads terminal and connection data from Excel files. Creates a transport graph with terminals as nodes and the connections between them as edges. Calculates distances between terminals based on their geographic coordinates. Searches for departure and arrival terminals in Warsaw and Madrid. Finds optimal routes according to two criteria: <ul style="list-style-type: none"> The shortest distance between terminals. The smallest number of reloadings. <p>This script allows you to dynamically plan intermodal transport based on real data. We can extend it with additional criteria, such as costs or transport time, if you need it.</p>	<p>[script] This script first defines a function <code>great_circle_distance</code> to calculate the distance between two terminals based on their latitude and longitude. Then, it loads the terminal and connection data, and creates a graph where the nodes are the cities and the edges represent the connections between them. The <code>find_shortest_route</code> function takes the start city, end city, and mode ('distance' or 'connections') as arguments. If the mode is 'distance', it calculates the great circle distance between connected cities and sets these distances as edge weights in the graph. Then, it uses the <code>nx.shortest_path</code> function to find the shortest path based on the edge weights. If the mode is 'connections', it finds the shortest path based on the number of connections (hops) between the cities. Finally, the script defines the start and end cities, calls the <code>find_shortest_route</code> function for both modes, and prints the resulting routes. This is a basic example, and it can be further improved by considering additional factors such as time windows, cost, and capacity constraints.</p>

Source: own work.

In the next step, the two solutions were compared to enable self-improvement of the developed route planning logic. An interesting aspect was the reaction of both models to the alternative logic proposed by the other LLM in creating the route plan.

4.2. LLM Confrontation and Self-improvement

Gemini Advanced responded in an interesting way when presented with the logic and results generated by GPT-4o.

Gemini Advanced: *It seems that ChatGPT 4.0's response is more accurate and relevant to the task. Its script correctly identifies the terminals in Warsaw and Madrid from the terminals dataset and uses the `geopy.distance.geodesic` function to calculate the distance between terminals, which is a more accurate approach than the `great_circle_distance` function I used. Additionally, ChatGPT 4.0's script correctly handles the connections between terminals by using the `city_stop` column from the terminals connections dataset to create edges in the graph. This approach ensures that the connections between terminals are properly represented in the graph, allowing for accurate route planning. While my script was able to generate routes based on the provided data, it did not correctly identify the specific terminals in Warsaw and Madrid, and it used a less accurate distance calculation method. Therefore, ChatGPT 4.0's response is a more accurate and complete solution to the task. I am still under development, and I am always learning. I will try my best to improve my performance on this type of task in the future.*

It was surprising that Gemini Advanced fully acknowledged that its previous solution was incorrect and completely accepted the solution proposed by GPT-4o. However, in a subsequent attempt to determine the route, Gemini Advanced generated the exact same configuration as before. The situation was different with GPT-4o. In its analysis of the responses, GPT-4o identified both strengths and weaknesses in both solutions (Table 9).

Table 9.

Weaknesses and strengths shown by GPT 4o based on LLMs results and logic comparison

	GPT 4o (LLM 1) solution	Gemini Advanced (LLM 2) solution
Advantages	<ul style="list-style-type: none"> • Taking into account real distances - I use <code>geopy.distance.geodesic</code>, which ensures accuracy in calculating the distances between terminals. • Work with full data - both terminals and connections are included, no shortcuts to city level. • Use of a directed graph (DiGraph) - in intermodal transport, rail and road connections can be one-way. Taking direction into account improves the realism of the model. 	<ul style="list-style-type: none"> • Using Haversine to calculate distances - enables efficient calculations for large data sets. • Data breakdown at the city level - the model treats connections more globally, which can improve results on a macro scale. • Minimizing the number of reloadings - the model takes into account direct connections between cities, which is useful in logistics.
Disadvantages	<ul style="list-style-type: none"> • I do not take into account the multi-level hierarchy of terminals - each city can have several terminals, but I only choose one at random. • No support for international connections with greater granularity - e.g. I do not analyze different travel options from Warsaw to Madrid through different countries. • I didn't use Haversine - I use <code>geopy</code>, but Haversine's formula would allow for more efficient large-scale calculations. • I don't check different operators - there could be alternative routes with better times, but different operators. 	<ul style="list-style-type: none"> • Lack of directionality in the graph – some connections are unidirectional, and the model doesn't account for this. • Doesn't account for all city terminals – the model looks at cities, not specific terminals, which can lead to errors. • Incorrect assignment of city names to connections – the code has trouble splitting <code>city_stop</code> correctly, which can create incorrect connections. • Lack of support for travel costs and times – the model only optimizes by distance or the number of transfers.

Source: own work.

Additionally, GPT-4o proposed a new computational logic aimed at eliminating the previously identified weaknesses. However, despite this adjustment, it ultimately generated the same route connections as before.

4.3. Checking the Final Routes

In the next stage, the selected LLMs were used to generate an interactive transport map, onto which the optimized route was overlaid. The transport route map generated by GPT-4o, based on its results, is presented in Figure 2.

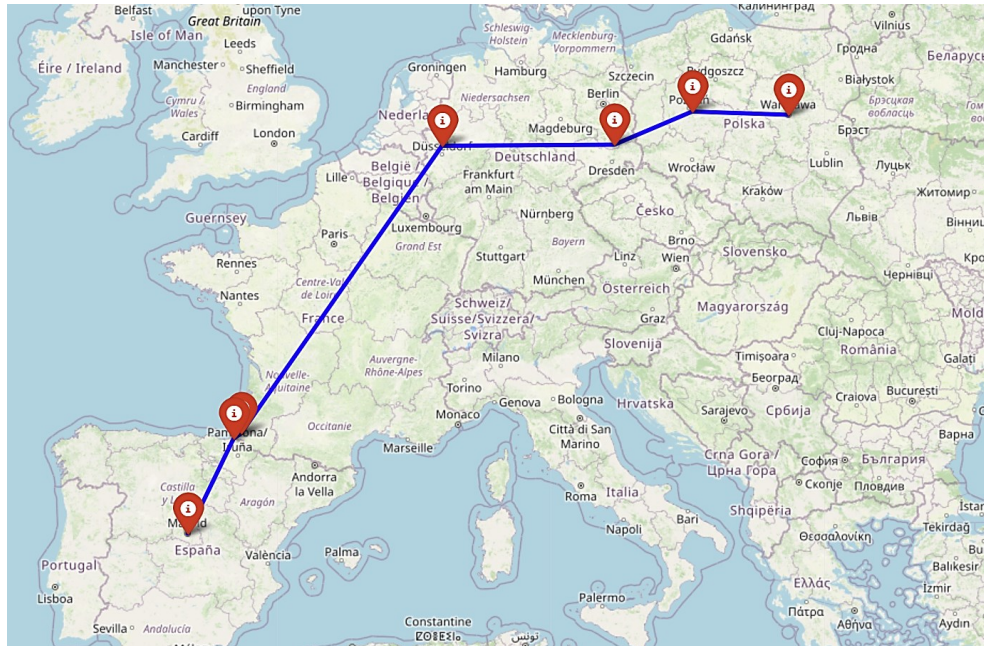


Figure 2. Intermodal transport route with reloading points.

Source: own work based on GPT-4o model.

Meanwhile, Gemini Advanced was unable to generate a visual solution on its own, so this task was again assigned to GPT-4o. Interestingly, GPT-4o identified an issue in which the second LLM provided only approximate transshipment terminal locations. GPT-4o proposed to fix the problem by searching for the nearest terminals in the given locations and then generating the corrected transport map, presented in Figure 3.

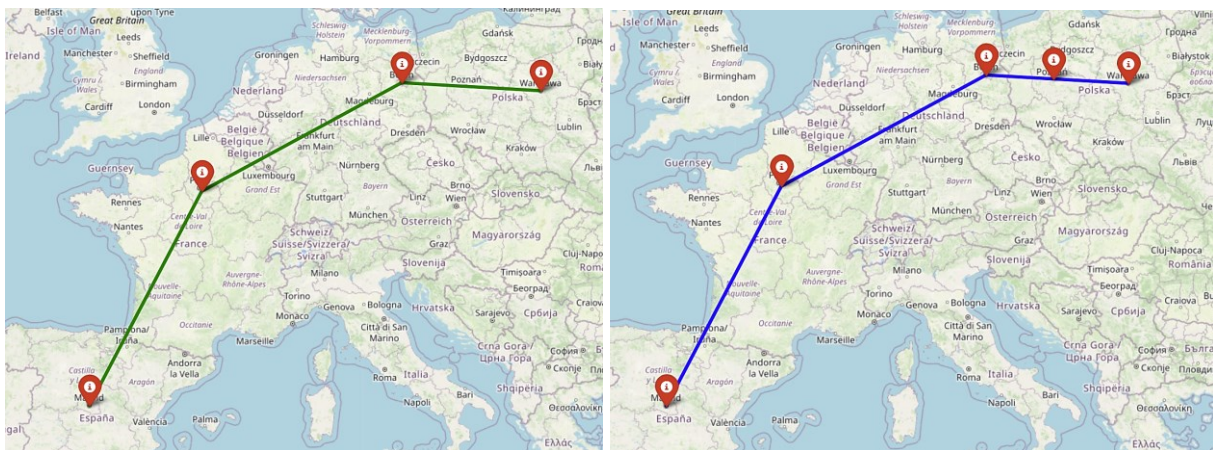


Figure 3. Intermodal transport route with reloading points – minimal reloading points (left side) and minimal distance (right side).

Source: own work based on Gemini Advances model (route description) and GPT-4o model (route description detailing and visualization).

Visually, the generated routes appear relatively similar. In the next step, a detailed analysis of their accuracy was conducted. This accuracy analysis involved a manual verification of the generated connections using the databases on which they were based. The connections generated by GPT-4o were correct, and all routes were feasible within the provided dataset.

However, the routes generated by Gemini Advanced contained inaccuracies: in the distance-minimizing route, it was impossible to establish a connection between the designated terminal in Warsaw (Poland) and Poznań (Poland) and in the transshipment-minimizing route, a connection between Warsaw (Poland) and Berlin (Germany) could not be completed.

5. Discussion

5.1. Route Planning in Intermodal Transport Using LLMs

The results of the study clearly indicate that the use of large language models (LLMs) such as GPT-4o and Gemini Advanced can significantly enhance the route planning process in intermodal transport. A key aspect of the study was the synergistic use of both models, where each LLM not only generated its own solutions but also evaluated and optimized the output of the other model. During the experiment, two route optimization scenarios were tested between Warsaw (Poland) and Madrid (Spain):

- Minimizing the number of transshipments – important for reducing operational costs and improving logistical efficiency.
- Minimizing distance – aimed at reducing total transport time and lowering CO₂ emissions.

A comparison of the results showed that GPT-4o generated solutions incorporating real intermodal terminals and connections, thanks to the use of a more precise distance calculation method (`geopy.distance.geodesic`). In contrast, Gemini Advanced focused on optimization at the city level, simplifying the analysis but sometimes leading to incorrect routes. The analysis demonstrated that LLMs can effectively identify optimal routes, but they require additional validation mechanisms to avoid generating infeasible connections due to limited database context.

The experiment confirms that LLMs can support route management in intermodal transport, but their application requires integration with real-world transport management systems (TMS) and the inclusion of additional factors such as delivery time constraints and infrastructure availability. An interesting aspect of the study was the use of two independent models for mutual evaluation. The analysis revealed that Gemini Advanced accepted GPT-4o's solution as superior, indicating that its own optimization approach needed improvement. In contrast, GPT-4o conducted a comparative analysis, identifying strengths and weaknesses of both models and proposing improvements in decision-making processes. Despite the significant benefits of using LLMs in route planning, the study revealed several key challenges. First one is lack of full integration with real-time operational data – the models operate based on provided datasets but cannot dynamically account for schedule changes or terminal closures. Second one

is need for additional validation of results – some routes suggested by the models were not feasible, highlighting the necessity of expert or TMS verification. Last one is the "black box" problem of AI – While LLMs generate effective solutions, it is not always clear which factors influenced their decisions, posing a challenge for their explainability.

5.2. Theoretical Contributions

Incorporating LLMs into transport route optimization challenges the traditional paradigm of logistics modeling, which has long relied on deterministic or heuristic frameworks. It opens the door to context-aware, adaptive decision-making that better reflects operational uncertainty. Existing literature primarily focuses on the use of heuristic algorithms and integer programming in intermodal route planning (Akyüz et al., 2023; Chen et al., 2014). In contrast, LLM-based approaches can expand these frameworks by enabling dynamic transport scenario generation and better adaptation to unpredictable operational conditions. In intermodal route optimization research, key algorithmic goals include minimizing costs, transport time, and the number of transshipments (Limbourg, Jourquin, 2009). Liu et al. (2020) demonstrated that traditional algorithms, such as Dijkstra's algorithm, can be effectively integrated with deep reinforcement learning to improve routing accuracy. The results of this study suggest that LLMs may represent the next step in this evolution—rather than relying solely on mathematical algorithms, AI models can be used for real-time operational analysis and optimal route recommendations. Furthermore, Román & Martín (2014) pointed out that traditional route planning methods often fail to account for passenger flexibility and customer preferences. In the context of intermodal logistics, LLMs can bridge this gap by analyzing large datasets of historical operations and customer preferences, enabling more precise route customization for carriers and clients.

Research on AI applications in intermodal logistics is increasingly appearing in academic literature (Akyüz et al., 2023; Abideen et al., 2023). Aungkulanon et al. (2024) emphasize that logistics innovation in the ASEAN region requires more advanced analytical methods, suggesting that LLMs could be used not only in route planning but also in cost prediction and infrastructure maintenance optimization. Meanwhile, Theeraviriya et al. (2019) studied logistics network optimization in terms of location selection and optimal transport routes. Their findings indicate that AI can play a key role in dynamically adjusting routes to operational changes and infrastructure constraints. Integrating LLMs with location-based models could therefore increase intermodal transport efficiency. Based on the study findings, further theoretical advancements are possible, including:

- Integrating LLMs with heuristic algorithms and classical optimization models – Liu et al. (2020) suggest that potential synergies between AI and heuristic methods could enhance route optimization performance, especially in dynamic logistics environments.
- Extending research to other transport sectors – Route optimization methods can be applied not only to intermodal transport but also to last-mile delivery and electric vehicle fleet management (Akyüz et al., 2023).

- Improving AI model explainability in logistics – One of the key challenges remains the interpretability of AI-generated results. There is a need for new methods to assess AI-driven decisions, as emphasized by Abideen et al. (2023) and Theeraviriya et al. (2019).

5.3. Practical Implications

The integration of LLMs into intermodal transport route planning carries several practical implications for 3PL operators, decision-makers, and transport management systems (TMS). The study results indicate that generative AI can contribute to operational efficiency, cost optimization, and improved transport service quality. Key practical takeaways include: dynamic route adaptation, optimized logistics strategies, decision support for transport managers and TMS integration. LLM-based systems can adjust transport routes based on changing conditions, leading to shorter delivery times and fewer transshipments. The dual-model approach (GPT-4o and Gemini Advanced) demonstrated that AI-generated route comparisons can result in more efficient logistics strategies. LLMs can analyze scenarios and recommend optimal routes, identifying potential risks, such as delays due to congested terminals. AI-driven models can enhance transport planning automation, providing real-time data insights and supplementing classical optimization algorithms.

5.4. Future Research Directions

The study findings suggest several potential directions for future research, contributing to further advancements in LLM applications in intermodal transport. Further research should focus on integrating LLMs with classical route optimization methods to enhance operational efficiency. The impact of LLMs on route optimization may vary based on transport infrastructure, requiring studies across different geographical contexts. Implementing LLM-based route planning in operational TMS systems would help assess their actual impact on logistics decision-making. Expanding research to last-mile delivery and urban transport optimization, where factors like traffic congestion and road availability play a crucial role.

6. Conclusions

This study focused on the integration of generative artificial intelligence, particularly GPT-4o and Gemini Advanced models, in optimization of intermodal transport routes, with a special emphasis on applications for 3PL operators. The results indicate the potential of large language models (LLMs) in supporting decision-making processes in intermodal logistics, offering both theoretical insights and practical implications. The study showed that LLMs can effectively generate optimized transport routes based on predefined objectives, such as

minimizing travel distance or reducing the number of transshipment points. A key finding was that the synergistic use of two models increases decision accuracy, as the models complement each other by identifying potential weaknesses in the generated solutions. GPT-4o demonstrated a greater ability to integrate real-world data on terminals and connections, whereas Gemini Advanced provided high-level optimization strategies but sometimes lacked detailed validation in the context of operational constraints. Despite these advantages, several limitations were identified. First, dependence on static datasets prevents LLMs from dynamically adapting to real-world disruptions, such as schedule changes or infrastructure failures. Second, some routes suggested by Gemini Advanced were found to be infeasible due to the lack of actual transport connections, emphasizing the need for precise validation mechanisms. Third, the "black box" nature of AI-generated decisions raises concerns regarding transparency and interpretability, which remains a significant challenge for implementing generative AI in logistics decision-making.

From a theoretical perspective, this study expands existing literature on intermodal transport optimization by introducing a new AI-driven approach. While traditional models rely on mathematical and heuristic algorithms, generative AI can dynamically adjust solutions to complex logistics environments. The findings suggest that further integration of LLMs with classical optimization algorithms could enhance their practical utility, particularly in real-world transport management systems. The practical implications for 3PL operators are significant. AI-supported route optimization can contribute to cost reduction, increased efficiency, and improved transport service quality. By using generative AI, logistics operators can partially automate the route planning process, identify inefficiencies, and propose alternative solutions based on dynamic conditions. However, the implementation of these technologies should be accompanied by robust validation mechanisms to ensure operational feasibility.

References

1. Abideen, A.Z., Sorooshian, S., Sundram, V.P.K., Musa, S. N. (2023). Collaborative insights on horizontal logistics innovation in supply chain management. *Journal of Open Innovation: Technology, Market, and Complexity*, 9(2), 100066. <https://doi.org/10.1016/j.joitmc.2023.100066>
2. Adelusola, M. (2024). *Shaping the future of supply chains: The role of generative AI and emerging technologies*. ResearchGate. <https://www.researchgate.net/publication/387531886>
3. Akyüz, M.H., Dekker, R., Sharif Azadeh, S. (2023). Partial and complete replanning of an intermodal transport network under disruptions. *Transportation Research Part E: Logistics and Transportation Review*, 169, 102968. <https://doi.org/10.1016/j.tre.2022.102968>

4. Anghinolfi, D., Paolucci, M., Sacone, S., Siri, S. (2011). *Integer programming and ant colony optimization for planning intermodal freight transportation operations*. Proceedings of the IEEE International Conference on Automation Science and Engineering.
5. Asimiyu, Z. (2024). *Revolutionizing supply chain efficiency: The transformative impact of generative AI on operations*. ResearchGate. <https://www.researchgate.net/publication/387531880>
6. Aungkulanon, P., Hirunwat, A., Atthirawong, W. (2024). Optimizing maintenance responsibility distribution for freight logistics in ASEAN. *Journal of Open Innovation: Technology, Market, and Complexity*, 10(1), 100239. <https://doi.org/10.1016/j.joitmc.2024.100239>
7. Baytak, A. (2024). The Content Analysis of the Lesson Plans Created by ChatGPT and Google Gemini. *Research in Social Sciences and Technology*, 9(1), 329-350.
8. Bhattacharya, A., Kumar, S.A., Tiwari, M.K., Talluri, S. (2014). An intermodal freight transport system for optimal supply chain logistics. *Transportation Research Part C: Emerging Technologies*, 38, 73-84.
9. Chang, T.S. (2008). Best routes selection in international intermodal networks. *Computers & Operations Research*.
10. Chen, K., Yang, Z., Notteboom, T. (2014). The design of coastal shipping services subject to carbon emission reduction targets and their external costs. *Transportation Research Part E: Logistics and Transportation Review*, 61, 192-211. <https://doi.org/10.1016/j.tre.2013.11.004>
11. Chen, X., Zuo, T., Lang, M., Li, S., Li, S. (2022). Integrated optimization of transfer station selection and train timetables for road–rail intermodal transport network. *Computers & Industrial Engineering*.
12. Deng, J., Lin, Y. (2022). The benefits and challenges of ChatGPT: An overview. *Frontiers in Computing and Intelligent Systems*, 2(2), 81-83.
13. Eftestøl, E.J., Bask, A., Rajahonka, M. (2014). Intermodal Transport research: A Law and Logistics Literature review with EU focus. *European Transport Law*, 49(6), 609-674.
14. Fosso Wamba, S., Guthrie, C., Queiroz, M.M., Minner, S. (2024). ChatGPT and generative artificial intelligence: an exploratory study of key benefits and challenges in operations and supply chain management. *International Journal of Production Research*, 62(16), 5676-5696.
15. Goodarzi, A.H., Jabbarzadeh, A., Fahimnia, B., Paquet, M. (2024). Evaluating the sustainability and resilience of an intermodal transport network leveraging consolidation strategies. *Transportation Research Part E: Logistics and Transportation Review*, 188, 103616.
16. Günay, S., Öztürk, A., Yiğit, Y. (2024). The accuracy of Gemini, GPT-4, and GPT-4o in ECG analysis: A comparison with cardiologists and emergency medicine specialists. *The American Journal Of Emergency Medicine*, 84, 68-73.

17. Hosseini, S., Al Khaled, A. (2021). Freight flow optimization to evaluate the criticality of intermodal surface transportation system infrastructures. *Computers & Industrial Engineering*.
18. Ji, Z., Yu, T., Xu, Y., Lee, N., Ishii, E., Fung, P. (2023, December). Towards mitigating LLM hallucination via self reflection. In: *Findings of the Association for Computational Linguistics: EMNLP 2023* (pp. 1827-1843).
19. Kleinová, K., Straka, M. (2024). Streamlining distribution routes using the language model of artificial intelligence. *Sustainability*, 16(6890). <https://doi.org/10.3390/su16166890>
20. Kmiecik, M. (2023). ChatGPT in third-party logistics—The game-changer or a step into the unknown? *Journal of Open Innovation: Technology, Market, and Complexity*, 9(4), 100174.
21. Li, B., Zhang, H., Wang, M., Han, S., Peng, S. (2024). Cooperative strategies of emission reduction in the 3PL-led supply chain. *IMA Journal of Management Mathematics*, dpae003.
22. Li, L., Negenborn, R.R., De Schutter, B. (2015). Intermodal freight transport planning—A receding horizon control approach. *Transportation Research Part C: Emerging Technologies*, 60, 77-95.
23. Li, L., Wang, J., Wang, H., Jin, X., Du, L. (2023). Intermodal transportation hub location optimization with government subsidies under the Belt and Road Initiative. *Ocean and Coastal Management*.
24. Limbourg, S., Jourquin, B. (2009). Optimal rail-road container terminal locations on the European network. *Transportation Research Part E: Logistics and Transportation Review*, 45(4), 551–563. <https://doi.org/10.1016/j.tre.2008.12.003>
25. Liu, S., Jiang, H., Chen, S., Ye, J., He, R., Sun, Z. (2020). Integrating Dijkstra's algorithm into deep inverse reinforcement learning for delivery route recommendation. *Transportation Research Part E: Logistics and Transportation Review*, 142, 102070. <https://doi.org/10.1016/j.tre.2020.102070>
26. Martino, A., Iannelli, M., Truong, C. (2023, May). *Knowledge injection to counter large language model (LLM) hallucination*. European Semantic Web Conference. Cham: Springer Nature Switzerland, pp. 182-185.
27. McIntosh, T.R., Susnjak, T., Liu, T., Watters, P., Halgamuge, M.N. (2023). *From google gemini to openai g*(g-star): A survey of reshaping the generative artificial intelligence (ai) research landscape*. arXiv preprint arXiv:2312.10868.
28. Mohamed, O.A.M. (2024). *How generative AI is transforming supply chain operations and efficiency*. Master's Thesis. Politecnico di Milano.
29. Pedersen, M.B. (2005). *Optimization models and solution methods for intermodal transportation*. Technical University of Denmark.
30. Prakash, S., Mehta, U., Sharma, B. (2024). *Artificial Intelligence-Driven Multimodal Route Planning: Addressing Dynamic Unavailability and Disruptions*. IEEE Access.

31. Qi, Z., Fang, Y., Zhang, M., Sun, Z., Wu, T., Liu, Z., Zhao, H. (2023). *Gemini vs GPT-4V: A Preliminary Comparison and Combination of Vision-Language Models Through Qualitative Cases*. arXiv preprint arXiv:2312.15011.
32. Rane, N., Choudhary, S., Rane, J. (2024). Gemini versus ChatGPT: applications, performance, architecture, capabilities, and implementation. *Performance, Architecture, Capabilities, and Implementation, February 13, 2024*.
33. Román, C., Martín, J.C. (2014). Integration of HSR and air transport: Understanding passengers' preferences. *Transportation Research Part E: Logistics and Transportation Review, 71*, 129-141. <https://doi.org/10.1016/j.tre.2014.09.001>
34. Rosyida, E.E., Santosa, B., Pujawan, I.N. (2020). Freight route planning in intermodal transportation network to deal with combinational disruptions. *Cogent Engineering*.
35. Sahin, B., Yilmaz, H., Ust, Y., Guneri, A.F., Gulsun, B., Turan, E. (2014). An approach for economic analysis of intermodal transportation. *The Scientific World Journal, 1*, 630320.
36. Sawadogo, M., Anciaux, D., Roy, D. (2012). *Reducing intermodal transportation impacts on society and environment by path selection: A multiobjective shortest path approach*. IFAC Symposium on Information Control Problems in Manufacturing.
37. Theeraviriya, C., Pitakaso, R., Sillapasa, K., Kanchanasuntorn, K. (2019). Location decision making and transportation route optimization in supply chain networks. *Journal of Open Innovation: Technology, Market, and Complexity, 5(2)*, 27. <https://doi.org/10.3390/joitmc5020027>
38. Wang, R., Yang, K., Yang, L., Gao, Z. (2018). Modeling and optimization of a road–rail intermodal transport system under uncertain information. *Engineering Applications of Artificial Intelligence, 72*, 423-436.
39. Wei, J., Yao, Y., Ton, J.F., Guo, H., Estornell, A., Liu, Y. (2024). *Measuring and reducing llm hallucination without gold-standard answers via expertise-weighting*. arXiv preprint arXiv:2402.10412.
40. Xu, S.X., Cheng, M., Huang, G.Q. (2015). Efficient intermodal transportation auctions for B2B e-commerce logistics with transaction costs. *Transportation Research Part B: Methodological, 80*, 322-337.
41. Xu, Z., Zheng, C., Zheng, S., Ma, G., Chen, Z. (2024). Multimodal transportation route optimization of emergency supplies under uncertain conditions. *Sustainability*.
42. Ye, Y., Zhao, Z., Liu, L., Feng, J., Du, J., Pei, Q. (2024). Federated generative artificial intelligence empowered traffic flow prediction under vehicular computing power networks. *IEEE Internet of Things Magazine*. <https://doi.org/10.1109/IOTM.001.2300259>
43. Zhang, R., Xiong, K., Du, H., Niyato, D., Kang, J., Shen, X., Poor, H.V. (2024). Generative AI-enabled vehicular networks: Fundamentals, framework, and case study. *IEEE Network, 38(4)*, 1-15. <https://doi.org/10.1109/MNET.2024.3391767>

44. Zhao, Y., Ioannou, P.A., Dessouky, M.M. (2019). Dynamic multimodal freight routing using a co-simulation optimization approach. *IEEE Transactions on Intelligent Transportation Systems*.
45. Zografos, K.G., Regan, A.C. (2004). Current challenges for intermodal freight transport and logistics in Europe and the United States. *Transportation Research Record, 1873(1)*, 70-78.