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GENERATIVE AI ROLE IN BUILDING 3PL COMPANIES' RESILIENCE

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Purpose: The purpose of this study is to evaluate the impact of generative artificial intelligence (gen-AI) models on the operational resilience of third-party logistics (3PL) companies. The research explores how gen-AI supports 3PL companies in adapting to changing market conditions, managing supply chain disruptions, and building resilience across various operational dimensions.
Design/methodology/approach: This study adopts the Analytical Hierarchy Process (AHP) methodology, integrating expert feedback to prioritize the influence of gen-AI models on four key resilience criteria: flexibility, velocity, collaboration and integration, and agility. Experts assessed the role of six gen-AI model types in enhancing these criteria.
Findings: The study found that agility (0.322) and velocity (0.309) were the most significant criteria for enhancing 3PL resilience, underscoring the importance of rapid adaptation and operational flexibility in logistics. Among the six evaluated gen-AI models, Model 5, which generates sounds (such as speech or music) from text, consistently ranked highest across all criteria, particularly for flexibility and velocity. This suggests that sound-based AI technologies can play a crucial role in automating dynamic processes and real-time communications in 3PL operations.
Research limitations/implications: The study was limited by a relatively small sample size and focused on four key criteria, which may have impacted the comprehensiveness of the findings. Future research could expand the analysis by incorporating additional criteria and increasing the respondent pool to minimize biases. Investigating the reasons for Model 5's dominance and exploring why Model 6 (code and algorithm generation) scored lowest could offer deeper insights into the evolving role of AI in logistics.
Originality/value: This study provides novel insights into the application of gen-AI in enhancing the resilience of 3PL companies. It highlights the strategic importance of AI-driven sound generation in logistics operations and offers a structured framework for prioritizing AI model investments. The findings are valuable for logistics companies, supply chain managers, and decision-makers aiming to optimize their operations and enhance resilience through AI technology.
Keywords: 3PL (third-party logistics), AHP (Analytic Hierarchy Process), generative AI, resilience.
Category of the paper: Research paper.

1. Introduction

Third-Party Logistics (3PL) companies must continuously strive to enhance their operational resilience to effectively manage disruptions and ensure continuity of operations. In the era of technological advancement, generative artificial intelligence (gen-AI) is playing an increasingly pivotal role in building resilience by supporting logistics processes at various levels, from communication automation to operations optimization. Research shows that the use of AI in logistics can significantly improve the flexibility and agility of operations, which is crucial for 3PL companies facing the growing complexity of global markets (Rahman et al., 2021; Zhu et al., 2022; Toorajipour et al., 2021). Gen-AI, with its advanced machine learning algorithms, enables logistics companies to automate processes, generate content, and optimize operations in real time. Its ability to process large data sets and support decision-making in dynamic operational conditions makes it an indispensable element of modern logistics (Ellaturu, Rajalakshmi, 2024; Liu, Lee, 2018). The choice of this research topic stems from the growing need to understand how gen-AI can support the resilience of 3PL companies. Operating in increasingly complex and disruption-prone supply chains, these companies require tools that allow them to quickly react and adapt their operations.

Generative AI may be the solution to these challenges, but there is a need for a detailed examination of its impact on the resilience of 3PL companies. Therefore, the following research question has been formulated:

RQ.1: What is the impact of gen-AI models on the resilience of 3PL companies?

This question forms the basis of the present analysis, which aims to evaluate how various generative AI models can support the operational resilience of 3PL companies, particularly in terms of their ability to adapt to changing market conditions and respond to disruptions in supply chains.

2. Theoretical background

2.1. Gen-AI in logistics processes

We have witnessed dynamic developments in industry and services in past years. Artificial intelligence has undoubtedly been a significant catalyst for change. Companies strive to gather as much information as possible from all processes, allowing them to tailor their products or services to meet customer needs (Eggert et al., 2011). To maximize profits, firms seek ways to manage data most efficiently. In the era of Industry 4.0, generative artificial intelligence has become an indispensable part of intelligent manufacturing, increasing automation rates, and improving process efficiency. (Peres et al., 2020) Its proficiency in processing large data sets and generating human-like text has significantly facilitated communication between humans and machines. (Rane, Nitin et al., 2023)

Artificial intelligence can be defined as a subdiscipline of computer science that focuses on a systematic approach to data processing, performing functions typically similar to human intelligence, such as reasoning, learning, and self-improvement. However, a universally accepted definition of this term still needs to be created (ISO, 2017).

Artificial intelligence has become indispensable in automating and digitizing supply chain operations (Dolgui, Ivanov, 2021). Specifically, its integration into supply chain management fundamentally alters prevailing business practices and managerial responsibilities. A 2018 Gartner report identified AI as the most crucial strategic technology. The report forecasted that global investment in AI-based applications would surpass $50.2 billion by 2021, and international revenue from the AI market would reach $2.59 trillion by the same year (Gartner, 2018; Statista, 2018).

Over time, AI has come to be defined as a scientific field focused on creating intelligent machines capable of performing tasks that typically require human intelligence, such as understanding language, recognizing patterns, learning, and solving problems (Kilani et al., 2022). AI is crucial in analyzing large datasets, employing scientific techniques, particularly machine learning, to identify decision-making patterns and minimize human intervention (Aggarwal et al., 2022). AI and algorithmic decision-making significantly impact daily life, with applications in healthcare, business, government, education, and justice, steering us towards a more algorithm-driven society (Kaur et al., 2022). Advancements in technology have led to the rise of Generative Artificial Intelligence (gen-AI), focusing on creating systems capable of generating new data that resemble original data, such as texts, images, or sounds, in a manner indistinguishable from human-created data Yu and Guo, 2023). Future gen-AI tools will likely train on data from the Internet, blending original and AI-generated data, prompting questions about the evolution or degradation of these tools (Martínez et al., 2023). Generative AI models encompass a variety of technologies, each with distinct characteristics and applications. It usually is about the models which allow to (Gonzalo-Brizuela et al., 2023; Knott et al., 2023; Kmiecik, Skórnóg, 2024):

- Models capable of generating text responses to questions or commands using advanced machine learning techniques.
- Models can transform text into images using sophisticated generative AI techniques to create realistic and detailed visuals.
- Models specialize in converting text into three-dimensional images, offering new computer graphics and design possibilities.
- Models focus on transforming images into text, enabling the creation of descriptions and narratives based on visual data.
- Models capable of generating videos from text, opening new avenues in film production and animation.

- Models specialize in generating sound from text, applicable in speech synthesis and music creation.
- Models focus on transforming text into programming code, aiding developers in automating and optimizing coding processes.
- Models designed to generate scientific texts, supporting researchers in creating and editing publications.
- Models that create new algorithms, pushing the boundaries of automation and innovation in algorithmics.
- Models producing text and images, representing a significant advancement in AI technology.

Authors assume that mentioned models could be gathered into six basic gen-AI models types:

- Models which generate text responses from commands.
- Models which generate images from text.
- Models which generate text from images.
- Models which generate videos from text.
- Models which generate sounds (speech or music) from text.
- Models which generate programming code and/or algorithms from text.

The business world is experiencing a technological revolution, with AI playing a crucial role in transforming operations and competition (Sestino et al., 2022). Generative AI, a particularly dynamic AI area, fosters innovation and creativity across various sectors (Haughes et al., 2021). Its applications in e-commerce and finance enhance customer experiences and business operations, making them more efficient and market driven. On a global scale, AI introduces new models of cooperation and competition among companies, significantly impacting international business relationships. According to Pallathadka et al. (2023) and Xiaong et al. (2020) AI and ML-based technologies are applied in: sales management and forecasting, fraud detection and security management, improving customer experience in e-commerce and finance and optimizing manufacturing processes, developing new forms of business cooperation and competition, business social network development and strategic human resource management. Modern scientific literature highlights the diverse applications of generative artificial intelligence models across various fields. These models, products of ongoing AI research and development, reflect a deepening understanding of technology. Their diversity enables a broad spectrum of applications, from simple tasks to complex processes requiring advanced analysis. Significantly, these models drive development and innovation in many sectors, shaping the technological future. As AI evolves, these models are expected to become more sophisticated, offering new capabilities and applications across an even wider range of domains. In logistics, the incorporation of Generative Artificial Intelligence (gen-AI) holds significant potential for enhancing operational efficiency, improving decision-making, and increasing resilience. As logistics companies navigate complex supply chains, gen-AI can transform how they manage and optimize their processes. Example logistics processes and areas of logistics concern supported by gen-AI could be:

- demand forecasting (Skórnóg, Kmiecik, 2023).
- assortment management (Kmiecik, 2023).
- supply chain operations improving (Frederico, 2023)
- improving operations due to Industry 4.0 perspective (Javaid et al., 2023).
- logistics operation costs reduction (Haddud, 2024).

One of the most interesting issues connected with these manuscripts is how gen-AI could influence logistics companies' resilience.

2.2. 3PL companies resilence

Logistics companies play a crucial role in today's global market. They are responsible for efficiently managing the flow of goods, data, and information (Shaharudin et al., 2014; Shanker et al., 2022). Their role and significance constantly evolve with technological advancements, especially in the context of emerging generative artificial intelligence (gen-AI). Technologies with potential for mass application in logistics can be divided into those whose wider deployment is forecasted for less than 5 years (robotics and automation, the Internet of Things, cloud logistics, big data analytics, augmented reality, and low-cost sensor solutions) and those for more than 5 years (autonomous vehicles, artificial intelligence, 3D printing, unmanned aerial vehicles, blockchain, next-generation wireless networks, bionic enhancements, virtual reality, and digital twins). Mass personalization is also being added to the mentioned technologies as one of the concepts related to innovation in logistics (Liu et al., 2018). One of the biggest trends in logistics companies is the attempt to implement blockchain-based technology (Tiwari et al., 2023). Third-party logistics (3PL) companies define themselves through a wide range of activities, including planning, executing, and controlling the flow and storage of goods, services, and information from the point of origin to the endpoint (Hazen et al., 2014). Their activities encompass domestic and international transportation, inventory management, warehousing, order fulfillment, and the management of information and finances related to these processes.

Regarding competitiveness, 3PL companies constantly strive to gain a competitive advantage. In a highly competitive market, logistics companies often focus on achieving leadership positions in a given niche (Yildiz, 2017). Outsourcing is most often associated with 3PL and 4PL (fourth-party logistics). 3PL companies offer comprehensive logistics services, including transportation, warehousing, inventory management, packaging, and other related services (Selviaridis, Spring, 2007). The use of modern technology is also frequently integral to the operations of logistics enterprises. Authors often emphasize that innovation is central to the business models of logistics enterprises, and recent years have confirmed the increased growth of innovation within logistics companies (Lagorio et al., 2022). In an era of increasing competition and dynamic technological changes, logistics companies must continuously adapt their business models and services to enhance their resilience to disruptions. The authors believe that the integration of gen-AI in logistics can open new opportunities to increase the resilience of these companies in today's market. In the literature, there are a lot of factors that influence positively on 3PL companies' resilience in the contemporary supply chain (table 1).

Table 1.
3PL companies' resilience factors

Example papers	Proposed 3PL companies' resilience factors based on logistics' resilience literature
Finck, Tillmann (2022)	Flexibility, recovery plans
Juttner, Maklan (2011)	flexibility, velocity, visibility, and collaboration
Ivanov, Dolgui (2021)	redundancy, real-time monitoring, visibility, and recovery plans
Wieland, Wallenberg (2013)	agility and robustness
Liu et al. (2018)	risk management culture, agility, integration
Deng, Noorliza (2023)	external integration
Gkanatsas, Krikke (2020)	operational risk and black swan events handling, reverse operations handling

Source: own elaboration.

According to the presented table, the following 3PL companies' resilience factors could be distinguished: flexibility; velocity, visibility, collaboration, redundancy, real-time monitoring, recovery plans, agility, robustness, risk management culture, internal integration, external integration, black swans events handling, reverse operation handling.

- Flexibility means the ability to quickly and efficiently adapt to changing conditions and customer needs. (Stevenson, Spring, 2007)
- Velocity refers to the time needed for change and the pace of change in the face of threats, risks, and potential disruptions (Jüttner, Maklan, 2011)
- Visibility is the capacity to have a clear view of supply chain operations and information. It enables better inventory management and response to environmental conditions Caridi et al., 2014).
- Collaboration indicates the extent to which a company works closely with partners, suppliers, and customers to ensure smooth operations (Barratt, 2004).
- Redundancy involves having backup systems, processes, or resources in place to ensure continuity in case of disruptions (Sheffi, 2005).
- Real-time monitoring is the ability to access and process information instantly, facilitating immediate decision-making and response (Ngai et al., 2008).
- Recovery plans involve pre-established strategies and procedures to restore normal operations after a disruption or emergency (Chopra, Sodhi, 2014).
- Agility is the ability to quickly adjust operations and strategies in response to unexpected changes or challenges in demand or supply (Yusuf et al., 2004).

- Robustness refers to the strength and reliability of a company's processes and systems to withstand disruptions or uncertain without significant impact (Tang, 2006).
- Risk management culture emphasizes proactive identifying, assessing, and mitigating risks to ensure smooth supply chain operations (Manuj, Mentzer, 2008).
- Internal integration is the degree of coordination and communication among different departments within the company (Flynn et al., 2010).
- External integration refers to seamless interaction and cooperation with external partners, suppliers, and customers to make the supply chain more effective (Frohlich, Westbrook, 2001).
- Handling black swan events involves the preparedness and strategies in place to deal with highly unpredictable and rare disruptive events (Taleb, 2007).
- Reverse operation handling is the capability to effectively manage reverse logistics, such as returns, recycling, and disposal (Guide et al., 2009).

3. Methods

3.1. Data collection

In this study, expert feedback was integral to assessing the defined criteria, ensuring a broad spectrum of perspectives was considered. A structured questionnaire was created based on five principal conceptual drivers identified through a combination of industry expertise and academic literature. To reduce the necessary number of responses in the conducted survey research and increase the likelihood of obtaining more responses, the authors decided to reduce the selected factors enhancing the resilience of 3PL and to compress gen-AI models based on their similar functionalities. In the scientific article, the evaluation criteria were reduced to four key factors: flexibility, velocity, collaboration and integration, and agility. This decision was made based on their overarching importance and their ability to incorporate other criteria:

- Flexibility is a fundamental aspect of supply chain management as it enables quick and efficient adaptation to changing conditions and customer needs. It includes aspects such as redundancy and recovery plans, as it allows companies to adjust to unforeseen situations by implementing backup systems and strategies to restore normal operations after disruptions.
- Velocity refers to the time needed to implement changes and the pace of changes in the face of threats, risks, and potential disruptions. It integrates elements such as real-time monitoring and visibility, as rapid adaptation requires current access to accurate information and the ability to make immediate decisions.

- Collaboration and integration are crucial for the smooth functioning of the supply chain, encompassing both cooperation with external partners (external integration) and internal coordination within the company (internal integration). This criterion also includes a risk management culture and the ability to handle black swan events, as effective collaboration and integration with partners and internal departments allow for a more comprehensive approach to identifying, assessing, and mitigating risks.
- Agility is key to quickly adjusting operations and strategies in response to unexpected changes or challenges related to demand or supply. It integrates aspects such as robustness and the ability to handle reverse operations, as strong and reliable processes and systems enable efficient disruption management and effective handling of returns, recycling, and disposal.

Mentioned approach to resilience main factors is similar to approach presented in Maghroor et al. (2024), where the main factors are divided into: agility, visibility, flexibility, collaboration and information sharing.

In building the survey, gen-AI models were also aggregated based on their functionalities into the following models:

- Model 1 (generate text responses from commands).
- Model 2 (generate images from text).
- Model 3 (generate text from images).
- Model 4 (generate videos from text).
- Model 5 (generate sounds (speech or music) from text).
- Model 6 (generate programming code and/or algorithms from text).

To gather the necessary input, an Analytical Hierarchy Process (AHP) survey was used. The survey utilized a linguistic scale for evaluating pairwise comparisons. Participants (table 2) were asked to compare the importance of each criterion relative to the others, translating their qualitative judgments into a quantitative framework to the others, translating their qualitative judgments into a quantitative framework

Table 2.
Brief description of experts

Expert	Years of experience in 3PL company*	Current position**	Size of enterprise***
1	4-6 years	Senior-level	Large
2	7-10 years	Senior-level	Large
3	1-3 years	Mid-level	Large
4	4-6 years	Managerial	Medium
5	4-6 years	Senior-level	Small
6	1-3 years	Mid-level	Large
7	1-3 years	Mid-level	Small

* Ranges in years: 1-3; 4-6; 7-10; above 10.
** Current position: Mid-level; Senior-level; Managerial; Executive.
*** Depends of number of employees: Mikro (1-9); Small (10-49); Medium (50-250); Large (above 250).

Source: own elaboration.

The AHP methodology facilitated a detailed and systematic approach to integrating expert evaluations, thereby strengthening the overall analysis and ensuring a thorough consideration of the criteria.

3.2. The Aanalytic Hierarchy Process (AHP)

The Analytical Hierarchy Process (AHP), introduced by Saaty (1980), is a well-established approach in multi-criteria decision-making (MCDM) due to its structured methodology. AHP effectively decomposes complex decision problems into hierarchical levels, including objectives, criteria, sub-criteria, and alternatives, facilitating a thorough evaluation (Saaty, 1980). In this study, AHP was employed to evaluate the impact of Generative AI models on supply chain resilience, focusing on four main criteria: Flexibility, Velocity, Collaboration and Integration, and Agility. For each criterion, six models were compared to prioritize the best-performing models. In implementing AHP, the decision-making process begins with constructing a hierarchical model of the problem, outlining various levels such as the main goal, primary dimensions, and subordinate criteria (Mondragon et al., 2019). This is followed by pairwise comparisons, where decision-makers assess the relative importance of each criterion using Saaty’s scale, which ranges from 1 (equal importance) to 9 (extremely more important), with intermediate values for varying degrees of preference (Mathiyazhagan et al., 2015).

The nine-point scale offers a detailed framework for capturing preferences. It enables decision-makers to express subtle differences in importance between criteria, ranging from "equally important" to "extremely more important" (Saaty, 2008). However, Prusak et al. (2016) note that the complexity of this scale can lead to inconsistencies. When decision-makers are presented with numerous options, distinguishing between nearly similar levels of preference can be challenging, potentially affecting the reliability of the results (Ishizak et al., 2011).

In practice, simpler scales are often preferred because they are easier to understand and apply (Chan, Chan, 2004). For instance, using a reduced number of scale points can enhance consistency by reducing cognitive load, especially when the decision-making process involves a limited set of criteria (Basak, 2011). This adjustment can be particularly beneficial when the practitioners involved are accustomed to different assessment methods.

In this study, the primary criteria for assessment include Flexibility, Velocity, Collaboration and Integration, and Agility. To evaluate these criteria, pairwise comparison matrices were developed based on expert judgments.

The experts provided their assessments using a custom scale of (Strong Importance, Moderate Importance, and Equal Importance). To ensure consistency with the Analytical Hierarchy Process (AHP) methodology, these judgments were converted into Saaty's standard scale, which ranges from 1 to 9. This conversion aligns with the AHP framework, allowing for a standardized comparison of the criteria. The pairwise comparison matrices were constructed to quantify the relative importance of each criterion. By applying Saaty's scale, which provides a range of values from "equally important" (1) to "extremely more important" (9), the converted judgments facilitate a structured and comparative analysis.

In the next step, the focus shifts to calculating the eigenvalue and eigenvector to determine the relative importance of each attribute. This process begins with the computation of the Geometric Mean (GM) of the pairwise comparison matrix, which simplifies the calculation of the highest eigenvalue.

The Geometric Mean method is employed to aggregate the judgments provided in the pairwise comparison matrix. This method involves calculating the geometric mean of the values in each row of the matrix, which helps in deriving the importance weights for each criterion. By doing so, the method simplifies the subsequent determination of the highest eigenvalue, which is crucial for assessing the consistency and accuracy of the decision-making model.

The eigenvalue and eigenvector calculations enable the derivation of priority weights for each attribute, facilitating a structured and quantifiable evaluation process within the AHP framework.

An essential component of AHP is assessing the consistency of the pairwise comparisons. Inconsistencies can arise from subjective biases, so the consistency ratio (CR) is calculated to evaluate the reliability of the judgments. To ensure the validity of the matrices, the consistency index (CI) and consistency ratio (CR) were calculated using the following formulas:

$$C.I. = \frac{\lambda_{max} - n}{n - 1},$$

$$C.R. = \frac{C.I.}{R.I.}$$

where CI is the consistency index and RI is the random index, which depends on the number of criteria (Saaty, 1980; Malczewski, 1999). A CR value greater than 0.10 suggests that the pairwise comparisons may be inconsistent, requiring revision (Feizizadeh et al., 2014).

The Analytic Hierarchy Process (AHP) was used to evaluate and prioritize the role of Generative AI in enhancing the resilience of third-party logistics (3PL) companies. The similar approach, but with Fuzzy AHP method was presented previously by Maghoor et al. (2024) to examine the gen-AI role in supply chain resilience. The analysis considered four key criteria: Flexibility, Velocity, Collaboration and Integration, and Agility. By constructing an aggregated pairwise comparison matrix, the AHP methodology provided a basis for deriving normalized priority vectors (weights) for these criteria, allowing for a structured evaluation of the impact of Generative AI on 3PL resilience (figure 1).

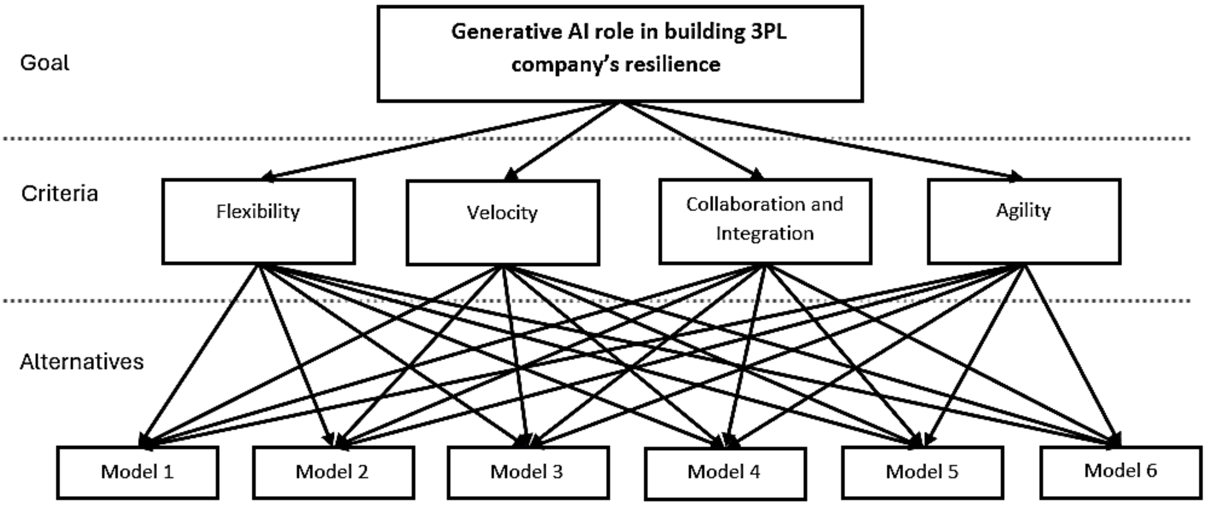

Figure 1. AHP structure.

4. Results

4.1. Criteria weights and consistency analysis

The aggregated pairwise comparison matrix (table 3) for the four criteria resulted in the following normalized priority vector: Flexibility (0.205), Velocity (0.309), Collaboration and Integration (0.164), and Agility (0.322). The Consistency Ratio (CR) for this matrix was 0.0209, which is below the threshold of 0.1, indicating that the judgments were consistent and reliable.

The priority vector (figure 2) suggests that Agility (0.322) and Velocity (0.309) are the most significant criteria for enhancing the resilience of 3PL companies through Generative AI. Agility, which refers to the ability to quickly respond to changes in the supply chain environment, and Velocity, which emphasizes speed and efficiency, are key factors in building a robust and responsive 3PL operation. Flexibility (0.205) and Collaboration and Integration (0.164) are also important but were given less priority by the experts, highlighting the need for adaptability and seamless cooperation among stakeholders in the logistics network.

Table 3.
Aggregated Pairwise Comparison Matrix for Criteria

Criteria	Flexibility	Velocity	Collaboration and Integration	Agility	Priorities
Flexibility	1.000	0.743	1.104	0.855	**0.205**
Velocity	1.346	1.000	1.219	1.219	**0.309**
Collaboration and Integration	0.906	0.820	1.000	0.464	**0.164**
Agility	1.170	0.820	2.155	1.000	**0.322**
λ_{max} = 4.056, CI = 0.0188, CR = 0.0209					

Source: own elaboration.

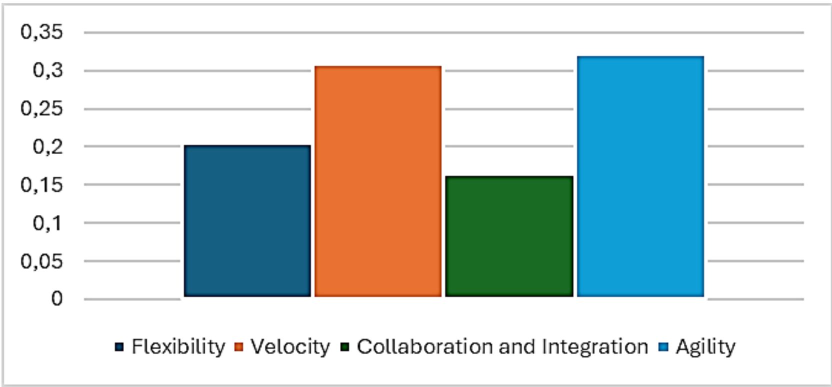

Figure 2. Priorities for criterias.

Source: own elaboration.

4.2. Model weights under each criterion

The AHP analysis also calculated the weights of various Generative AI models under each criterion to determine their effectiveness in building resilience within 3PL companies. Each model's weight was calculated based on aggregated expert judgments, with consistency checks confirming the reliability of the results.

4.2.1. Flexibility

The weights for the models under the Flexibility criterion were: Model 1 (0.088), Model 2 (0.185), Model 3 (0.171), Model 4 (0.184), Model 5 (0.295), and Model 6 (0.078). The CR for this criterion was 0.0081, indicating consistent judgments. Model 5 showed the highest weight (0.295), suggesting it is the most effective in enhancing flexibility in 3PL operations, allowing companies to adapt to varying demand and supply conditions. Aggregated pairwise comparison matrix is shown in table 4 and the priorities are shown in the figure 3.

Table 4.

Aggregated Pairwise Comparison Matrix for Models under Flexibility

Flexibility	F-Model 1	F -Model 2	F -Model 3	F -Model 4	F -Model 5	F -Model 6	Priorities
F-Model 1	1.000	0.424	0.581	0.424	0.313	1.258	**0.088**
F-Model 2	2.358	1.000	1.076	0.855	0.679	2.358	**0.185**
F-Model 3	1.723	0.930	1.000	1.170	0.424	2.536	**0.171**
F-Model 4	2.358	1.170	0.855	1.000	0.679	2.015	**0.184**
F-Model 5	3.192	1.472	2.358	1.472	1.000	3.471	**0.295**
F-Model 6	0.795	0.424	0.394	0.496	0.288	1.000	**0.078**
λmax = 6.050 , CI = 0.0100, CR = 0.0081							

Source: own elaboration.

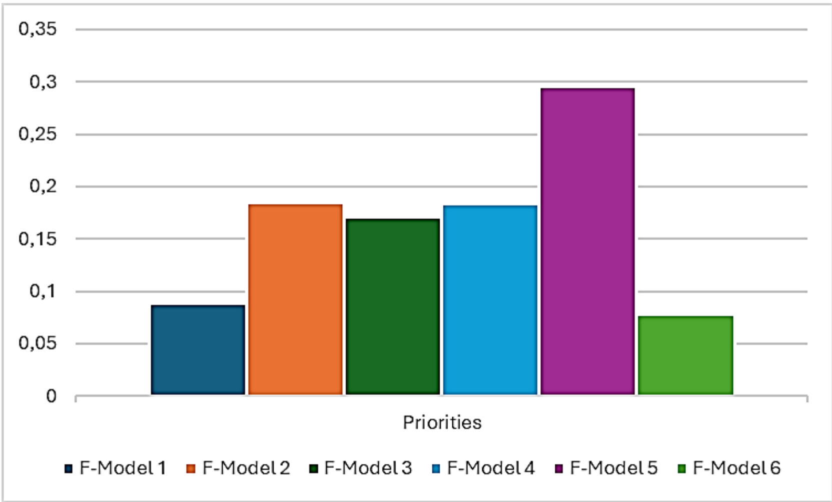

Figure 3. Priorities for flexibility.

Source: own elaboration.

4.2.2. Velocity

Under the Velocity criterion, the weights were: Model 1 (0.103), Model 2 (0.194), Model 3 (0.158), Model 4 (0.183), Model 5 (0.271), and Model 6 (0.091). The CR was 0.0077, which indicates high consistency in the expert judgments. Model 5 again scored the highest weight (0.271), highlighting its effectiveness in optimizing speed and efficiency in 3PL processes. Aggregated pairwise comparison matrix is shown in table 5 and the priorities are shown in the figure 4.

Table 5.

Aggregated Pairwise Comparison Matrix for Models under Velocity

Velocity	V-Model 1	V-Model 2	V-Model 3	V-Model 4	V-Model 5	V-Model 6	Priorities
V-Model 1	1.000	0.540	0.540	0.631	0.394	1.170	**0.103**
V-Model 2	1.853	1.000	1.170	0.855	0.855	2.358	**0.194**
V-Model 3	1.853	0.855	1.000	0.679	0.540	1.873	**0.158**
V-Model 4	1.584	1.170	1.472	1.000	0.581	1.601	**0.183**
V-Model 5	2.536	1.170	1.853	1.723	1.000	3.000	**0.271**
V-Model 6	0.855	0.424	0.534	0.624	0.333	1.000	**0.091**
λ_{max} = 6.048, CI = 0.0096, CR = 0.0077							

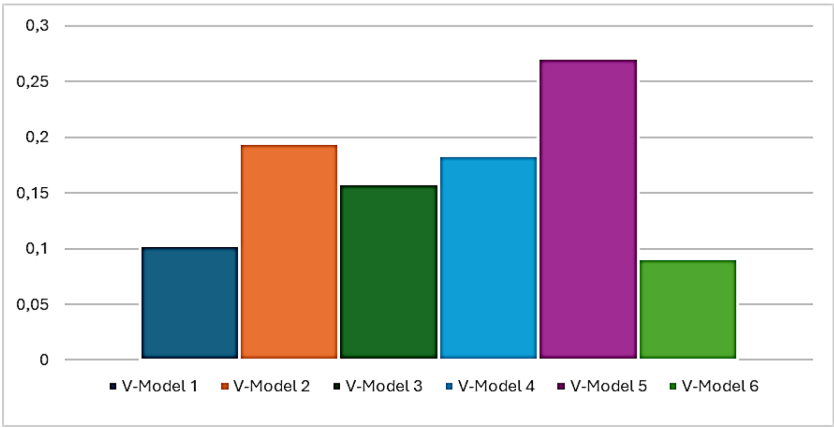

Figure 4. Priorities for velocity.

Source: own elaboration.

4.2.3. Collaboration and integration

For Collaboration and Integration, the weights were: Model 1 (0.095), Model 2 (0.163), Model 3 (0.203), Model 4 (0.221), Model 5 (0.253), and Model 6 (0.065). The CR was 0.0167, confirming consistency. While Model 5 maintained a strong position (0.253), Model 4 (0.221) and Model 3 (0.203) also demonstrated significant potential, suggesting their effectiveness in fostering collaborative relationships and integrating various supply chain functions. Aggregated pairwise comparison matrix is shown in table 6 and the priorities are shown in the figure 5.

Table 6.
Aggregated Pairwise Comparison Matrix for Models under Collaboration and Integration

Collaboration and Integration	CI-Model 1	CI-Model 2	CI-Model 3	CI-Model 4	CI-Model 5	CI-Model 6	Priorities
CI-Model 1	1.000	0.679	0.461	0.288	0.367	1.873	**0.095**
CI-Model 2	1.472	1.000	1.000	0.731	0.461	3.227	**0.163**
CI-Model 3	2.168	1.000	1.000	1.170	0.855	2.967	**0.203**
CI-Model 4	3.471	1.369	0.855	1.000	0.930	2.758	**0.221**
CI-Model 5	2.728	2.168	1.170	1.076	1.000	3.227	**0.253**
CI-Model 6	0.534	0.310	0.337	0.363	0.310	1.000	**0.065**
λ_{max} = 6.104, CI = 0.0207 , CR = 0.0167							

Source: own elaboration.

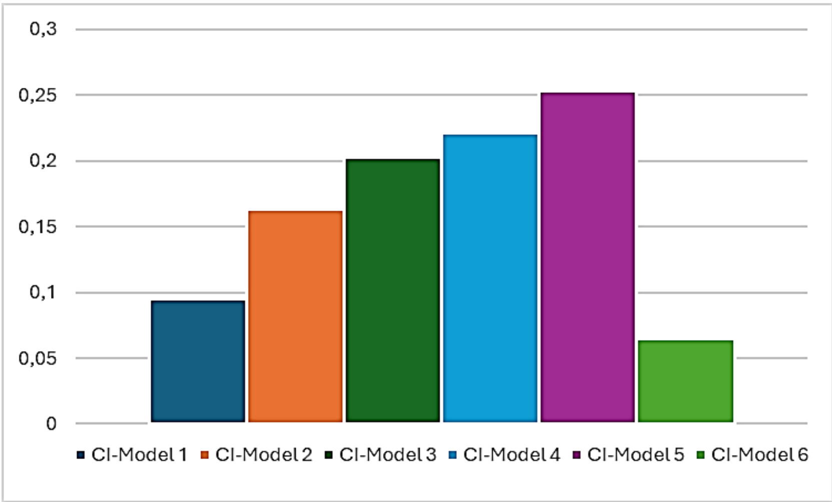

Figure 5. Priorities for velocity.

Source: own elaboration.

4.2.4. Agility

The model weights under the Agility criterion were: Model 1 (0.120), Model 2 (0.176), Model 3 (0.134), Model 4 (0.211), Model 5 (0.270), and Model 6 (0.089). The CR for this criterion was 0.0160, indicating consistent judgments. Model 5 (0.270) and Model 4 (0.211) emerged as the top models, underscoring their ability to enhance agility by enabling quick adaptation to changes in the logistics environment. Aggregated pairwise comparison matrix is shown in table 7 and the priorities are shown in the figure 6.

Table 7.
Aggregated Pairwise Comparison Matrix for Models under Agility

Agility	A-Model 1	A-Model 2	A-Model 3	A-Model 4	A-Model 5	A-Model 6	Priorities
A-Model 1	1.000	0.461	1.170	0.731	0.424	1.170	**0.120**
A-Model 2	2.168	1.000	1.000	0.855	0.679	1.601	**0.176**
A-Model 3	0.855	1.000	1.000	0.731	0.394	1.601	**0.134**
A-Model 4	1.369	1.170	1.369	1.000	0.930	3.000	**0.211**
A-Model 5	2.358	1.472	2.536	1.076	1.000	3.000	**0.270**
A-Model 6	0.855	0.624	0.624	0.333	0.333	1.000	**0.089**
λ_{max} = 6.099, CI = 0.0199, CR = 0.0160							

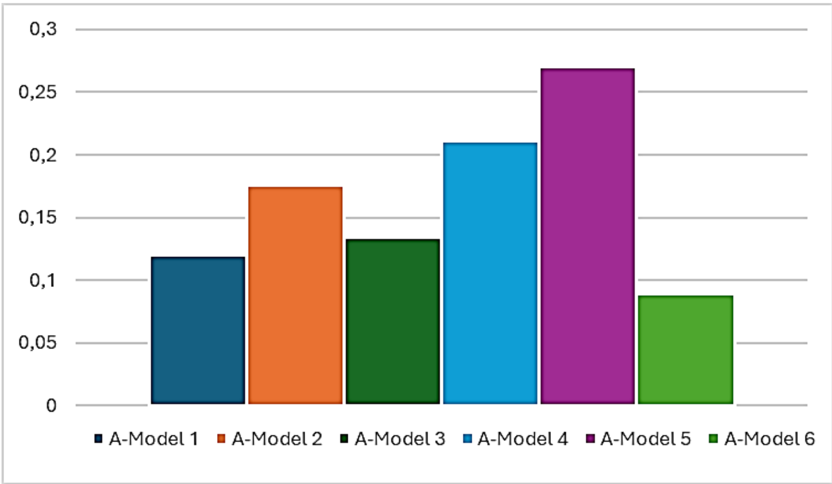

Figure 6. Priorities for agility.

Source: own elaboration.

4.3. Interpretation of results

The results indicate that Model 5 consistently outperformed other models across multiple criteria, particularly in Flexibility and Velocity, with the highest weights of 0.295 and 0.271, respectively. This suggests that Model 5 is particularly effective in enhancing the adaptability and speed of 3PL companies, which are crucial for resilience. Model 4 and Model 2 also performed well, especially under the Collaboration and Integration and Agility criteria, highlighting their potential to improve cooperation and rapid response capabilities within 3PL operations.

These findings provide important insights for decision-makers in 3PL companies seeking to enhance resilience through the adoption of Generative AI. Prioritizing Model 5 would likely yield the most significant benefits across key resilience dimensions, while Model 4 and Model 2 could be strong alternatives for specific operational focuses.

The AHP method effectively offered a structured framework for evaluating the role of Generative AI in building the resilience of 3PL companies. The consistency checks verified the reliability of the expert judgments, ensuring robust and valid findings. This study contributes valuable insights into how Generative AI can be leveraged to strengthen 3PL operations, guiding both academic research and practical decision-making in logistics management. Future research could explore additional criteria or incorporate alternative decision-making methods to refine and expand the analysis

5. Discussion

The results of the analysis confirm the key role of gen-AI in enhancing the resilience of 3PL companies providing logistics services. The AHP analysis showed that among the four criteria — flexibility, velocity, collaboration and integration, and agility — agility (0.322) and velocity (0.309) were the most important for building 3PL resilience, reflecting the significance of quickly adapting and responding to changing market and operational conditions. This finding addresses the research questions, indicating that operational efficiency in the context of 3PL logistics largely depends on the ability to react quickly and efficiently adjust processes in response to unforeseen challenges, such as supply chain disruptions. AI models, particularly Model 5 (generating sounds, such as speech or music from text), stood out in supporting the key aspects of flexibility and velocity. These results suggest that sound-based technologies can play an essential role in logistics by supporting dynamic processes like communication or the automation of real-time notifications. Interestingly, Model 5 received the highest weight in almost all analyzed criteria, indicating its versatility and potential to support various dimensions of operational resilience.

These data clearly respond to the research question regarding the role of gen-AI in building the resilience of 3PL companies. The results show that generative models, particularly those related to sound, can significantly impact process optimization and the velocity of response to supply chain disruptions. Rapid adaptation to changing market conditions and the ability to respond to unforeseen challenges, such as supply chain disruptions, are crucial for the operational efficiency of 3PL companies (Sullivan, Wamba, 2022; Belhadi et al., 2021). These findings align with previous studies highlighting the importance of agility and velocity in managing supply chain disruptions (Yandrapalli, 2023; Belhadi et al., 2021).

In the context of flexibility, generative AI has proven to be a critical element supporting dynamic processes, such as communication and real-time notification automation. Research indicates that AI-based technologies contribute to improving supply chain flexibility and adaptive capabilities, as confirmed by Yandrapalli's (2023) findings. The application of AI in automating communication processes can significantly enhance operational flexibility, which is key in changing market conditions.

In supply chain literature, Christopher and Holweg (2011) emphasize the importance of effective communication as a foundation for supply chain resilience. In our study, collaboration and integration were rated as less important than agility and velocity, suggesting that in dynamic market conditions, response speed and adaptability may take precedence over long-term collaboration (Richey et al., 2023). This may be surprising in the context of dominant theoretical approaches, which often emphasize collaboration as a key element of resilience.

One unexpected result of this study is the relatively lower weight assigned to the criterion of collaboration and integration (0.164) compared to the other criteria. Literature often highlights that collaboration and integration are crucial for building supply chain resilience, especially in the context of risk management (Richey et al., 2023). These findings may suggest that in the face of sudden disruptions, organizations may focus more on rapid adaptation and flexibility, leading to a shift in supply chain management approaches. A possible explanation for this result is that the experts involved in the study may have considered velocity and agility to have a more direct impact on 3PL responses to supply chain disruptions, particularly in the short term. In dynamic and changing market conditions, rapid action may be prioritized, and integration with partners or internal collaboration may be seen as less critical in situations requiring immediate response.

The results of this study have significant implications for both business practice and further theoretical research. From a practical standpoint, 3PL companies can leverage gen-AI, particularly in the area of sound generation (Model 5), to improve response velocity and agility in their logistics operations, including supporting offered value-added services (VAS). The implementation of such technologies can contribute to process automation, such as AI-based communication systems that notify real-time disruptions or further enhance well-known techniques like pick-by-voice in order picking. Moreover, Model 5 can support operational flexibility processes, enabling quick adjustments to changing market conditions and unforeseen disruptions. The development of research on various AI models and their impact on different resilience criteria can expand theoretical knowledge and provide practical insights for their implementation in various industries.

6. Conclusions

The aim of this article was to examine the impact of generative artificial intelligence (gen-AI) models on the resilience of 3PL companies. Based on the study conducted on an objective research group, the following conclusion is: The dominance of the Agility and Velocity factors over the Collaboration & Integration and Flexibility. Results suggest that 3PL companies primarily focus their resilience-building strategies on dynamic operational and tactical actions. This approach probably enables them to make decisions tailored to their needs in the specific moment. Further research is recommended to verify these assumptions and to explore how these factors influence company performance and the decision-making process. Additionally, the observed advantage of model 5 (models generating sounds, such as speech or music, from text) over other analyzed models is noteworthy. It may indicate an upcoming trend in the development of models for this type of company. A potential next step could be conducting detailed studies among experts to identify the reasons for this dominance and to understand why model 6 (models generating programming code and/or algorithms from text) achieved the lowest scores in the study.

The research can support 3PL companies in enhancing the resilience of their operations by leveraging appropriate gen-AI models. With targeted investments and solutions tailored to the specific needs of the companies connected with gen-AI, it is possible to improve key performance indicators and overall business outcomes. It is also important to note that the survey was conducted on a relatively limited sample size. To confirm these preliminary findings and minimize potential biases, it would be necessary to increase the number of respondents and ensure a well-structured participation of various respondent groups. The limitation of evaluation criteria to four key factors significantly influenced the results; therefore, future studies should consider a broader set of criteria to enable a more comprehensive analysis of the interactions between them.

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