A Comprehensive Framework for Selecting the Best Human-Centric Generative AI Model for Supply Chain Risk Management

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Abstract

Supply chain risk management is a critical challenge in today's increasingly complex and interconnected global markets, particularly within specific supply chains where disruptions can have far-reaching consequences. Generative Artificial Intelligence (GAI) transformer models have emerged as powerful tools for effectively managing these risks. However, selecting the most suitable GAI model for specific supply chain contexts remains a significant challenge due to the diverse range of available models and the complex interplay of risk factors involved. This challenge is further compounded by the necessity of considering human-centric criteria to ensure that the chosen model aligns with ethical standards and practical needs. This paper addresses this challenge by introducing an enhanced multi-criteria decision-making (MCDM) framework that refines the Evaluation based on Distance from Average Solution (EDAS) method. Our approach first improves the logical structure of the EDAS method and then incorporates the interactions and interdependencies between criteria, thereby overcoming key limitations of traditional MCDM methods and providing a more accurate and comprehensive evaluation process. We applied this improved EDAS model to the task of selecting the best GAI transformer model for risk management in the food supply chain. Through a systematic evaluation of various GAI models, considering their performance across multiple risk factors, our study identified GPT (Generative Pre-trained Transformer) as the most suitable model for this context, demonstrating superior capabilities in addressing the complex challenges associated with food supply chain risks. This research not only advances the theoretical foundation of MCDM techniques but also offers practical insights into the application of AI in supply chain management, highlighting the importance of human-centric AI approaches that prioritize transparency, ethical alignment, and effective decision-making.

Keywords: Supply chain risk management, Generative artificial intelligence, Processing, R. Graph, EDAS method

Abbreviation	Full Form
AI	Artificial Intelligence
ANN	Artificial Neural Network
BERT	Bidirectional Encoder Representations from Transformers
DL	Deep Learning

EDAS	Evaluation Based on Distance from Average Solution
EVAMIX	The EValuation of MIXed data
GAI	Generative Artificial Intelligence
GNN	Graph Neural Networks
GPT	Generative Pre-trained Transformer
IoT	Internet of Things
IV-SFS	Interval-Valued Spherical Fuzzy Sets
LSTM	Long Short-Term Memory
MABAC	Multi-Attributive Border Approximation Area Comparison
MADM	Multi-Attribute Decision Making
MCDM	Multi-Criteria Decision-Making
ML	Machine Learning
NLP	Natural Language Processing
RoBERTa	Robustly optimized BERT approach
SCOM	Supply Chain Operations Management
SCRM	Supply Chain Risk Management
T5	Text-To-Text Transfer Transformer
TODIM	Tomada de Decisão Interativa Multicritério
TOPSIS	Technique for Order of Preference by Similarity to Ideal Solution
VIKOR	Vlsekriterijumska Optimizacija I Kompromisno Resenje
WASPAS	Weighted Aggregated Sum Product Assessment
XAI	explainable AI

1. Introduction

In today's interconnected and dynamic global economy, supply chain management plays a pivotal role in ensuring the seamless flow of goods, services, and information from producers to consumers. The complexity and interdependencies within supply chains make them vulnerable to a variety of risks, including demand fluctuations, supply disruptions, and logistical challenges. Effective risk management is crucial to maintain the resilience, efficiency, and sustainability of supply chains [1]. Supply chains are inherently complex and involve numerous stakeholders, including suppliers, manufacturers, distributors, and retailers, each contributing to the overall flow of goods and services. This complexity introduces multiple points of vulnerability, making supply chains susceptible to a wide array of risks [2]. For instance, sudden shifts in consumer demand, geopolitical events, natural disasters, and supplier insolvencies can all disrupt the smooth operation of supply chains. Traditional risk management approaches often struggle to cope with these uncertainties due to their limited ability to process and analyze large volumes of data in real-time. The COVID-19 pandemic highlighted the fragility of global supply chains, underscoring the need for more resilient and adaptive risk management strategies. During the pandemic, many organizations faced unprecedented disruptions, leading to shortages of critical goods, delays in production, and significant financial losses [3].

Artificial Intelligence (AI) has emerged as a transformative technology offering novel solutions for enhancing supply chain risk management. AI has revolutionized many aspects of supply chain management by enabling better data analysis, improved decision-making, and enhanced operational efficiency [4]. AI technologies such as machine learning, predictive analytics, and natural language processing (NLP) are increasingly being utilized to optimize various supply chain processes. For example, machine learning algorithms can analyze historical data to forecast demand more accurately, while predictive analytics can help identify potential bottlenecks and optimize inventory levels [5]. AI-powered systems can also enhance supplier risk management by analyzing vast amounts of data to assess supplier reliability and predict potential disruptions. Furthermore, AI applications in logistics can improve route optimization, reducing transportation costs and delivery times. By leveraging AI, businesses can gain deeper insights into their supply chains, allowing for more proactive and informed decision-making [6]. One of the most promising subsets of AI that is gaining traction in supply chain risk management is Generative AI (GAI). GAI refers to a class of algorithms that can generate new data or predict future scenarios based on existing data. Unlike traditional AI models that primarily analyze and classify data, GAI creates new possibilities, making it particularly valuable for forecasting, scenario planning, and decision support in supply chain management. By leveraging vast amounts of data, GAI can identify patterns, anticipate disruptions, and propose proactive measures to mitigate risks, thereby enhancing the overall robustness of supply chains [7].

Several advanced methods within GAI, such as NLP and transformers, are particularly effective in supply chain risk management. NLP enables AI systems to understand and interpret human language, allowing for the analysis of unstructured data such as news articles, social media posts, and supplier communications, which is crucial for identifying potential risks and disruptions early on. For example, NLP can scan news reports for signs of political instability in supplier regions or monitor social media for customer sentiment about product shortages. These capabilities allow companies to anticipate disruptions and implement mitigation strategies proactively. Additionally, transformers, a type of deep learning model, have significantly enhanced the performance of NLP tasks by improving the understanding and generation of human language, thus enabling more accurate and efficient risk assessments. By leveraging these technologies, businesses can gain comprehensive insights into their supply chains, enhance decision-making processes, and maintain resilience in the face of unforeseen disruptions. For instance, during the COVID-19 pandemic, GAI techniques were instrumental in forecasting demand fluctuations and managing inventory, helping organizations navigate through unprecedented challenges [8]. Furthermore, AI-driven systems using generative models can simulate various supply chain scenarios, allowing businesses to explore different strategies and outcomes, thus better preparing for potential risks [9].

Transformers, a type of deep learning model, have revolutionized NLP by providing a framework for understanding context and relationships within text data. Models like GPT (Generative Pre-trained Transformer) can process and generate human-like text, making them ideal for predicting future scenarios based on historical data. In supply chain management, transformers can be used to simulate various risk scenarios and develop contingency plans, as well as enhance demand forecasting by analyzing complex patterns in large datasets (Fig. 1). Specific models such as BERT (Bidirectional Encoder Representations from Transformers), RoBERTa (Robustly optimized BERT approach), and T5 (Text-To-Text Transfer Transformer) have shown remarkable capabilities in understanding and generating human language, making them valuable for sentiment analysis, extracting insights from unstructured text, and various other applications.

In recent years, the high complexity and diverse capabilities of NLP and GAI methods have posed challenges for organizations in selecting the best approach for their supply chains to reduce risks. The choice of methods depends on various factors, such as organizational needs, supply chain nature, available data, and desired outcomes. Companies must evaluate trade-offs between models for tasks like demand forecasting, risk prediction, or supplier evaluation. Integration of these AI systems require significant investments in technology, skilled personnel, and ongoing maintenance to ensure effectiveness and adaptability. The rapid pace of AI advancements complicates the selection process, necessitating companies to stay updated and address issues related to data quality, privacy, and security. Therefore, a strategic approach involving thorough evaluation, testing, and continuous improvement is essential for leveraging AI to mitigate supply chain risks effectively.

Figure 1. Various applications of GAI in supply chain management

Another crucial issue for the most suitable GAI model for supply chain risk management is the consideration of human-centric factors. These include aspects such as data privacy measures, adherence to regulatory standards, tailored solutions for industry specifics, and the ease of model version control. These factors are essential because they directly influence how well the AI system aligns with human values, ethical principles, and practical operational needs. Ensuring robust data privacy is critical for maintaining user trust and safeguarding sensitive information, which is increasingly important in a world where data breaches can have significant consequences [10]. Adherence to regulatory standards is vital for ensuring that the AI operates within the legal and ethical boundaries set to protect societal interests, reinforcing the model's credibility and acceptability. Additionally, providing tailored solutions that consider industry-specific needs ensures that the AI's outputs are relevant and actionable for human decision-makers in various contexts. Finally, ease of model version control is important for enabling human operators to efficiently manage and update the AI system, ensuring that it remains adaptable and user-friendly over time. By prioritizing these human-centric considerations, organizations can enhance the effectiveness and ethical deployment of AI in managing supply chain risks, ensuring that the chosen model not only meets technical requirements but also respects and supports human stakeholders [11].

The aim of this study is to select the best GAI and transformer language model for supply chain risk management. To address the challenges of selecting the best NLP and GAI methods for supply chain risk management, one effective solution is the use of Multi-Criteria Decision-Making (MCDM) methods. MCDM methods help organizations evaluate and prioritize different options based on multiple criteria, ensuring a more comprehensive and balanced decision-making process. There are various MCDM methods, and in this article, we focus on the Evaluation Based on Distance from Average Solution (EDAS) method.

The EDAS method is recognized as a valuable MCDM technique for supply chain risk management, offering a systematic framework for assessing multiple risk factors simultaneously, thereby helping decision-makers identify the most suitable solution from a range of options [12]. However, EDAS does have certain limitations. It may not provide sufficient depth in comparative analyses in complex decision-making contexts, as it relies on mean evaluations, potentially leading to oversimplification. Therefore, modifications are necessary to refine EDAS, address its limitations, and improve the overall ranking procedure [13]. In addition, the EDAS method cannot consider interactions between criteria, which is a significant limitation in complex decision-making scenarios where criteria are often interdependent.

In this context, this paper introduces several significant and innovative contributions to the fields of supply chain risk management and multi-criteria decision-making (MCDM). First, we present an enhancement of the EDAS method by refining its logical foundation to better integrate it with the R.Graph method [14], which accounts for causal relationships within a chain of variables. . This includes the development of a novel approach that accounts for the interactions and interdependencies between criteria, which has traditionally been a limitation of the basic EDAS method. By integrating these interactions, we propose a new decision support framework that offers a more comprehensive and accurate evaluation process.

Second, we apply this improved model and methodology to the critical task of identifying the most effective GAI technique for supply chain risk management. Our proposed framework not only evaluates the performance of various GAI models but also considers the complex dependencies among different risk factors, providing decision-makers with a robust tool for selecting the most suitable AI methods. This dual contribution advances both the theoretical foundation of MCDM techniques and their practical application in the rapidly evolving landscape of supply chain risk management.

The current paper is organized into several sections, each addressing a specific aspect of the research. Section 2 provides a comprehensive survey of existing literature on causality models and supply chain resilience, highlighting key findings and gaps in current knowledge. In Section 3, the paper delves into the preliminaries explaining the fundamental concepts and mathematical formulations that underpin the research. Section 4 introduces the proposed method, detailing its construction, underlying assumptions, and theoretical framework. A relevant case study is presented in Section 5, demonstrating the practical application of the proposed model in a real-world context. Finally, Section 6 summarizes the key findings of the research, synthesizing the insights gained from the literature review, theoretical discussions, and case study analysis, and proposes directions for future research.

2. Literature review

Section 2.1 of the literature review examines the application of GAI in supply chain operations, detailing how these technologies optimize processes such as demand forecasting, inventory management, and logistics. Subsection 2.2 focuses on the use of GAI in supply chain risk management, highlighting its role in predicting and mitigating disruptions. Subsection 2.3 explores the integration of NLP and transformer models, which enhance communication and data analysis within supply chains. Finally, subsection 2.4 discusses the research gaps and potential areas for innovation, suggesting how future advancements could further transform the field.

2.1. Application of GAI in Supply Chain operations

In recent years, the integration of AI technologies in supply chain management has significantly transformed traditional practices. Particularly, the utilization of GAI has emerged as a powerful tool for optimizing various aspects of the supply chain. This literature review aims to explore the impact and potential applications of GAI in Supply chain operations

Demand forecasting plays a crucial role in supply chain and operations management, acting as the guiding force for inventory, production, and distribution choices [15]. In recent times, the significance of AI in enhancing this essential procedure has grown considerably. AI algorithms are now extensively employed for demand forecasting, utilizing large sets of data to decipher complex patterns and generate forecasts. By learning and adjusting over time, these AI models enhance the precision of forecasting and aid in the efficient management of operations, thereby optimizing the entire supply chain process [16]. Kantasa-Ard, et al. [17] introduced a method for predicting demand in intricate supply chains by utilizing a Long Short-Term Memory model, with its parameters adjusted through a combination of genetic algorithms and scatter search. Another area that has been addressed in recent years in the field of GAI in the supply chain is the distribution and transportation strategy. Huang et al. [18] focused on optimizing the shortest path interdiction problem, which is a major issue in the distribution and transportation strategy in SCOM. The main goal is to maximize the length of the shortest route that a follower can take, while taking into account a restricted interdiction budget. The study suggests a new approach that leverages AI tools, such as learning, prediction, interaction, and adaptation, to address the problem. Priore et al. [19] have reviewed a study on the user domain of GAI in supply chain design. The study sheds light on how AI can be utilized to streamline intricate scenarios, improving inventory management efficiency. It employs an inductive learning algorithm, an example of Supervised Learning, to construct a flexible framework. This framework enables the identification of optimal replenishment policies by effectively adjusting to changing conditions, showcasing AI's capacity for learning and adaptation. Integrating AI into learning and adaptation processes aligns seamlessly with the three-tier supply chain model outlined in this paper, which revolves around seven variables: cost structure, demand fluctuations, three lead times, and two partners' inventory policies.

2.2. Application of GAI in Supply Chain Risk Management

As the demand for efficient and resilient supply chain management grows, the application of General Artificial Intelligence (GAI) has garnered significant attention. This subsection aims to explore the existing body of knowledge on how GAI can be leveraged to mitigate supply chain risks and enhance overall operational performance. By examining recent studies and industry practices, this section seeks to provide valuable insights into the potential benefits and challenges associated with integrating GAI into supply chain risk management.

Managing risks within the supply chain entails implementing tactics to recognize, evaluate, alleviate, and supervise unforeseen circumstances that may have adverse effects on any segment of the supply chain. Given the necessity for swift and flexible decision-making rooted in extensive and intricate data reservoirs, the realm of supply chain risk management emerges as a fertile ground for the utilization of AI technologies [20]. Wong et al [21] highlighted the importance of AI, specifically its abilities in learning, predicting, and reasoning, in improving the effectiveness and flexibility of supply chain risk management, particularly for small and medium-sized businesses. The scientists utilized AI to investigate how it influences supply chain risk management, offering a distinct viewpoint based on the resource-based view. They utilized a comprehensive method that involved partial least squares-based structural equation modeling and artificial neural network, demonstrating AI's ability to learn from intricate data sets and derive valuable insights. Rashid [22] explored the integration of AI in supply chain risk management, emphasizing a proactive approach with AI augmenting human capabilities. The study highlights the shift towards early risk detection and continuous monitoring enabled by AI, reflecting market trends and offering businesses insights to benchmark their AI maturity in SCRM. GAI is widely used in mitigating supply chain risks, offering various tools and features that revolutionize the management of potential disruptions. By utilizing advanced algorithms, this technology can analyze large amounts of data, including historical and real-time information. He et al. [23] emphasized that GAI primarily serves in forecasted risk evaluation to alleviate risks. Through analyzing historical data, current patterns, and external influences, AI systems anticipate potential disruptions. Armed with such foresight, supply chain managers can devise strategies and implement preemptive measures to counteract potential disruptions proactively. In addition, supply chain operations can take advantage of simulations and scenario planning enabled by GAI [24]. This tool creates various risk scenarios by utilizing past and present data, aiding in the assessment of potential outcomes and development of tailored contingency plans for various risk types. These simulations are crucial for assessing the effectiveness of mitigation strategies. GAI's real-time monitoring capabilities offer a proactive approach to minimizing risks. By continuously analyzing supplier performance, market data, and IoT device data, AI algorithms can quickly detect deviations that may signal potential threats. This real-time surveillance allows for early intervention to prevent or mitigate disruptions. Additionally, GAI enables adaptive decision-making by providing dynamic insights into risk-relevant data, allowing for real-time adjustments to inventory levels, logistical routes, and supplier relationships in response to changing risk indicators. This agility empowers supply chain managers to swiftly address emerging risks and minimize their impact on operations [25]. Further enhancing this field, Yang et al. [26] proposed a machine learning model for financial risk prevention in supply chains, emphasizing the transformation of traditional supply chains into intelligent, smartly managed systems. Burstein and Zuckerman [27] presented a machine learning framework aimed at reducing human subjectivity in risk assessments, thus improving prediction accuracy. Lastly, Hung et al. [28] discussed the application of Bayesian networks in predicting supply chain risks, highlighting the improvement in resilience and continuity that such technologies offer. These recent studies underscore the transformative potential of GAI in supply chain risk management, illustrating various methodologies and technologies that contribute to more resilient and adaptive supply chain operations

2.3. Applications of NLP and transform models

The introduction of Transformers has greatly transformed the field of NLP. Since their debut in 2017, Transformers have become widely adopted and have significantly influenced NLP advancements. Bender et al. [29] analyzed the current trend in NLP of creating and utilizing larger language models like BERT, GPT-2/3, and Switch-C, questioning if size alone is driving progress. They offered recommendations to mitigate the risks of these models, including accounting for environmental and financial costs, carefully curating and documenting datasets, assessing how well the technology aligns with research and development goals and stakeholder values, and promoting research that goes beyond just scaling up language models. Other studies, such as the one by [30], have offered thorough overviews of specific NLP tasks like sentiment analysis. They highlight the potential of deep learning models in addressing these challenges by reviewing recent works that build models using term frequency–inverse document frequency and word embeddings. However, these reviews might miss concurrent and synergistic advancements by focusing solely on one task. Historically, NLP systems relied on transparent methods like rules and decision trees, which are naturally explainable. However, the rise of deep learning models has reduced their interpretability. This lack of transparency in AI systems can undermine trust, making explainable AI (XAI) an important area of focus in the field. Danilevsky et al. [31] conducted the first survey specifically focused on XAI in NLP, reviewing works presented at major NLP conferences over the past seven years. Deep learning models necessitate large datasets, posing a challenge for many NLP tasks, particularly in low-resource languages. Furthermore, these models demand substantial computing power. The growing interest in transfer learning stems from the need to address these limitations and leverage the extensive trained models now available. Alyafeai et al. [32] have explored the recent advancements in transfer learning within the NLP field. Another study by [33] explored the use of graph neural networks (GNNs) for NLP tasks. GNNs are similar to Transformers in their capacity to capture long-range dependencies and complex relationships between data entities. However, GNNs differ from traditional Transformers in their unique structure, modeling data explicitly as graphs and utilizing graph structures for computation and information propagation. In contrast, Transformers operate on flattened sequences, making them more suitable for processing language data. This distinction justifies a separate investigation of GNNs. The adoption of pre-trained language models, as discussed by Devlin et al. [34], has further revolutionized NLP by enabling models to leverage vast amounts of textual data to improve performance across various tasks. Their BERT model, in particular, introduced bidirectional training of Transformers, leading to significant advancements in understanding context in text processing. Furthermore, Liu et al. [35] introduced RoBERTa, an optimized version of BERT that demonstrates the importance of training techniques and hyperparameters in enhancing model performance, reinforcing the idea that model architecture alone is not sufficient for optimal results. Lastly, a study by Brown et al. [36] on GPT-3 highlighted the potential of scaling up language models, showcasing how increased parameters and training data can result in substantial improvements in various NLP benchmarks. Their research emphasizes the balance between model size, training data, and computational resources in pushing the boundaries of what NLP models can achieve

2.4. Research Gap and Innovations

Despite the significant advancements in AI and NLP technologies within supply chain risk management (SCRM), critical gaps remain. Traditional risk management approaches often struggle to handle the real-time analysis and large volumes of data required for modern supply chains. Moreover, selecting the most appropriate GAI and NLP methods for specific organizational needs is a complex task, given the diversity of available techniques. From machine learning algorithms to transformer-based generative models, each presents distinct strengths and limitations that complicate decision-making for businesses aiming to enhance risk mitigation strategies.

Although several studies [29-31] highlighted the potential of AI in supply chain contexts, there is a lack of comprehensive frameworks that guide organizations in selecting the best technologies effectively in their supply chain operations. Many current models fail to account for the complex, interrelated risk factors that influence decision-making in supply chains. They also neglect human-centric considerations such as data privacy, regulatory compliance, and real-time adaptability, which are crucial for aligning AI with organizational goals.

This study addresses existing gaps by proposing an integrated framework called the R.Graph-enhanced EDAS method**,** a novel approach that combines the strengths of the R.Graph method, which considers interactions between criteria, with the enhanced EDAS technique to overcome some limitations of the traditional EDAS method. By accounting for interdependencies among risk factors, this method provides a more refined decision-making framework, enabling businesses to visualize trade-offs and assess the relative performances of various AI models. In conclusion, the R.Graph-enhanced EDAS model fills the gap by offering a comprehensive decision-making framework that addresses the shortcomings of conventional AI selection models. It emphasizes both technical performance and human-centric criteria, ensuring that supply chains remain resilient, adaptable, and ethically aligned to meet contemporary challenges.

3. Preliminaries

This section is divided into two parts, each dedicated to a distinct methodological approach used in decision analysis and causal inference. The first part introduces the classical EDAS method. This method is a widely recognized MCDM technique that assesses alternatives based on their performance relative to the average solution across multiple criteria. It provides a structured approach to evaluating and ranking alternatives by calculating their distances from the average performance and incorporating both positive and negative distances. The second part discusses the R. Graph causal method, a technique designed to analyze the causal relationships between variables and events. Unlike the EDAS method, which focuses on performance evaluation, the R. Graph method is used to understand how changes in certain variables or the occurrence of specific events can influence other components within a system. This method involves constructing a causal graph where variables and events are represented as nodes, and their causal interactions are depicted as directed edges.

3.1. Classic EDAS method

The classic EDAS method is a systematic multi-criteria decision-making approach that involves creating a decision matrix with all alternatives and criteria. It calculates an average solution to serve as a benchmark, then determines Positive and Negative Distance from Average matrices based on the nature of the criteria (beneficial or cost-related). These distances are weighted, summed, and normalized to calculate an appraisal score for each alternative. Finally, the alternatives are ranked by their appraisal scores, with the highest score indicating the optimal choice, providing a thorough evaluation based on relative performance across various criteria.

Step 1: Creating the decision matrix (X) as illustrated below:

$$X = \begin{array}{c} \\ a_1 \\ a_2 \\ \vdots \\ a_m \end{array} \begin{array}{c} \begin{array}{cccc} c_1 & c_1 & \cdots & c_n \end{array} \\ \begin{pmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{pmatrix} \end{array} \tag{1}$$

Within the framework of the study, x_{ij} represents the performance measurement of the *i*-th alternative with respect to the *j*-th criterion. This method allows for an accurate evaluation of the performance of alternatives across multiple criteria, improving the decision-making process by providing a structured assessment of their strengths and weaknesses.

Step 2: Calculating the average solution across all criteria, as illustrated below:

$$x_{s_j} = \left[x_{s_j} \right]_{1\times n} \tag{2}$$

where

$$x_{s_j} = \frac{\sum_{i=1}^{n} x_{ij}}{n} \tag{3}$$

Step 3: Computing the Positive Distance from Average u and Negative Distance from Average l matrices based on the nature of the criteria (beneficial and cost) as shown below:

$$\begin{cases} u = [u_{ij}]_{m\times n} \\ l = [l_{ij}]_{m\times n} \end{cases} \tag{4}$$

where ${u_{ij}}^S$ and ${l_{ij}}^S$ represent the positive and negative distances of the i-th alternative from the average solution for the j-th criterion, respectively, and are determined as follows:

if $j-th$ criterion is beneficial, we have:

$$\begin{cases} {u_{ij}}^S = \frac{\max\left(0,\left(x_{ij} - x_{s_j}\right)\right)}{x_{s_j}} \\ {l_{ij}}^S = \frac{\max\left(0,\left(x_{s_j} - x_{ij}\right)\right)}{x_{s_j}} \end{cases} \tag{5}$$

If $j-th$ criterion is non-beneficial, we have:

$$\begin{cases} {u_{ij}}^S = \frac{\max\left(0,\left(x_{s_j} - x_{ij}\right)\right)}{x_{s_j}} \\ {l_{ij}}^S = \frac{\max\left(0,\left(x_{ij} - x_{s_j}\right)\right)}{x_{s_j}} \end{cases} \tag{6}$$

Step 4: At this stage, the weighted summation of u and l is calculated, and is expressed by Equations (10) and (11):

$$\begin{cases} SP_i = \sum_{j=1}^{m} w_j \, {u_{ij}}^S \\ SP_i = \sum_{j=1}^{m} w_j \, {u_{ij}}^S \end{cases} \tag{7}$$

Where SP_i indicates the weighted total of ${u_{ij}}^S$, and SN_i represents the weighted sum of ${l_{ij}}^S$ for the i-th alternative, with w_j representing the weight of the j-th criterion.

Step 5: The values of SP and SN are normalized, shown as follows:

$$\begin{cases} NSP_i = \frac{SP_i}{max_i(SP_i)} \\ NSN_i = \frac{SN_i}{max_i(SN_i)} \end{cases} \tag{8}$$

Step 6: The appraisal score (AS) is calculated for all the alternatives by using Eq (14):

$$AS_i = \frac{1}{2}\,(NSP_i + NSN_i) \quad 0 \le AS_i \le 1 \tag{9}$$

The normalized values of SP are indicated as NSP_i, whereas the normalized values of SN are represented as NSN_i.

Step 7: In this phase, the alternatives are ranked according to their decreasing Appraisal Scores (AS). The alternative with the highest AS is identified as the optimal choice among the candidate solutions.

3.2. R. Graph casual method

The R. Graph technique involves a fixed series of non-looping causal components that impact one another. Its purpose is to analyze the proportion of variation in each component resulting from shifts in other components or the emergence of distinct occurrences within a consistent timeframe, based on the assumption that these occurrences are guaranteed. Within this technique, the ideas are outlined as below [14]:

Variable: Any element capable of taking on a value and magnitude as its strength. When there exists a causal relationship between two variables, an alteration in the causal variable can result in a modification in the other variable. In the R. Graph approach, the i-th variable is represented as V_i and illustrated in the shape of a circle.

Event: An element that lacks a precise intensity or quantity and is typically depicted as either zero or one. The occurrence of such an event can initiate other events or result in alterations to the values of other variables. In the R. Graph method, event j is denoted as $E(j)$ and illustrated as a rectangle.

Factor: Each of the variables or events is termed a factor.

Parent: When there is a cause-and-effect relationship between two factors, the one that affects the other is called the parent.

Different scenarios of the effects of events and occurrences on each other are illustrated in Fig. 2, and a type of R. Graph is shown in Fig. 3.

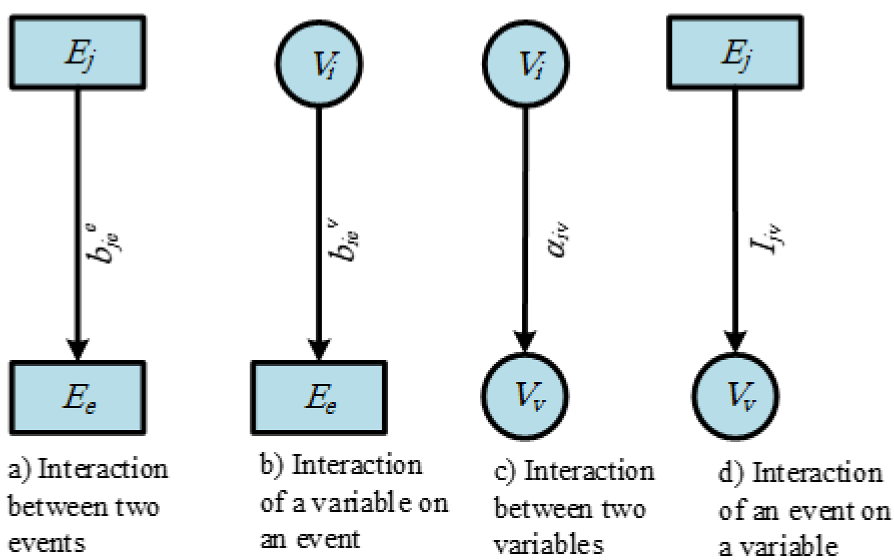


Figure 2.Different scenarios of influence in deterministic R.Graph method

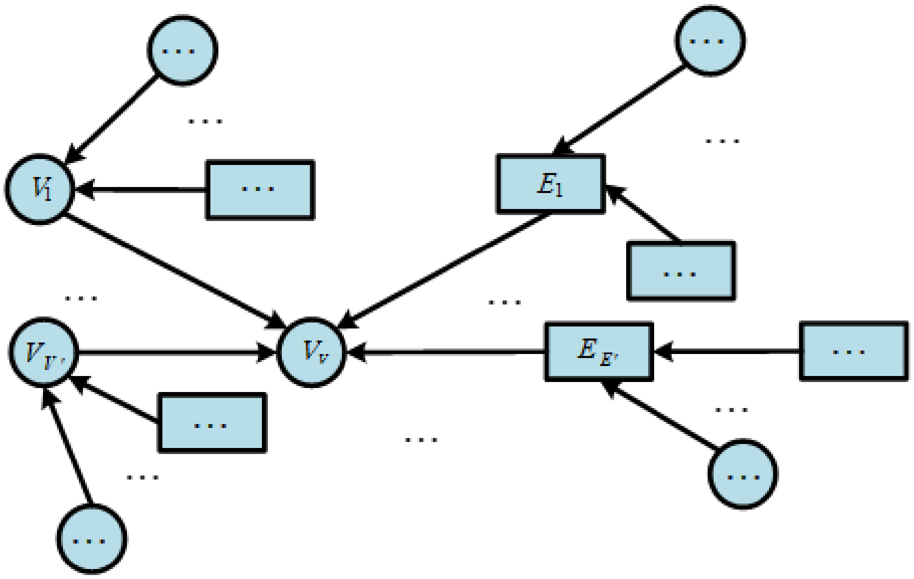


Figure 3.A typical R.Graph diagram

Definition 1: In the R. Graph method, risks or deviations are defined as the exact deviation of a parameter from its modified value, which can be calculated using Equations (15) and (16) [35].

$$R = \frac{|Changed\ value\ - Initial\ value|}{Initial\ value} \tag{10}$$

where, if e_2 denotes the changed value and e_1 denotes the initial value, the risk (effect) value is calculated using Equation (16).

$$R = \frac{|e_2 - e_1|}{e_1} \qquad R \geq 0 \tag{11}$$

Definition 2. In the R.Graph method, the way of influencing different factors is represented through the R.Graph matrix ($R^{R.Graph}$) as follows [35]:

$$R^{R.Graph} = \left[\begin{array}{cc}
V-V = \begin{array}{c|c} & \begin{array}{cccccc} \boldsymbol{V_1} & \boldsymbol{V_2} & \dots & \boldsymbol{V_v} & \dots & \boldsymbol{V_V} \end{array} \\ \begin{array}{c} \boldsymbol{V_1} \\ \boldsymbol{V_2} \\ \dots \\ \boldsymbol{V_v} \\ \dots \\ \boldsymbol{V_V} \end{array} & \begin{bmatrix} 0 & \alpha_{12} & \dots & \alpha_{1v} & \dots & \alpha_{1V} \\ \alpha_{21} & 0 & \dots & \alpha_{2v} & \dots & \alpha_{2V} \\ \dots & \dots & 0 & \dots & \dots & \dots \\ \alpha_{v1} & \alpha_{v2} & \dots & 0 & \dots & \alpha_{vV} \\ \dots & 0 & \dots & \dots & 0 & \dots \\ \alpha_{V1} & \alpha_{V2} & 0 & \alpha_{Vv} & \dots & 0 \end{bmatrix} \end{array}
&
V-E = \begin{array}{c|c} & \begin{array}{cccccc} \boldsymbol{E_1} & \boldsymbol{E_2} & \dots & \boldsymbol{E_e} & \dots & \boldsymbol{E_E} \end{array} \\ \begin{array}{c} \boldsymbol{V_1} \\ \boldsymbol{V_2} \\ \dots \\ \boldsymbol{V_v} \\ \dots \\ \boldsymbol{V_V} \end{array} & \begin{bmatrix} b_{11}{}^{v} & b_{12}{}^{v} & \dots & b_{1e}{}^{v} & \dots & b_{1E}{}^{v} \\ b_{21}{}^{v} & b_{22}{}^{v} & \dots & b_{2e}{}^{v} & \dots & b_{2E}{}^{v} \\ \dots & \dots & \dots & \dots & \dots & \dots \\ b_{v1}{}^{v} & b_{v2}{}^{v} & \dots & b_{ve}{}^{v} & \dots & b_{vE}{}^{v} \\ \dots & \dots & \dots & \dots & \dots & \dots \\ b_{V1}{}^{v} & b_{V2}{}^{v} & \dots & b_{Ve}{}^{v} & \dots & b_{VE}{}^{v} \end{bmatrix} \end{array}
\\
E-V = \begin{array}{cc} \begin{array}{c} \boldsymbol{E_1} \\ \boldsymbol{E_2} \\ \dots \\ \boldsymbol{E_e} \\ \dots \\ \boldsymbol{E_E} \end{array} & \begin{bmatrix} 0 & b_{12}{}^{e} & \dots & b_{1e}{}^{e} & \dots & b_{1E}{}^{e} \\ b_{21}{}^{e} & 0 & \dots & b_{2e}{}^{e} & \dots & b_{2E}{}^{e} \\ \dots & \dots & 0 & \dots & \dots & \dots \\ b_{e1}{}^{e} & b_{e2}{}^{e} & \dots & 0 & \dots & b_{eE}{}^{e} \\ \dots & \dots & \dots & \dots & 0 & \dots \\ b_{E1}{}^{e} & b_{E2}{}^{e} & 0 & b_{Ee}{}^{e} & \dots & 0 \end{bmatrix} \end{array}
&
E-E = \begin{array}{cc} \begin{array}{c} \boldsymbol{E_1} \\ \boldsymbol{E_2} \\ \dots \\ \boldsymbol{E_e} \\ \dots \\ \boldsymbol{E_E} \end{array} & \begin{bmatrix} 0 & b_{12}{}^{e} & \dots & b_{1e}{}^{e} & \dots & b_{1E}{}^{e} \\ b_{21}{}^{e} & 0 & \dots & b_{2e}{}^{e} & \dots & b_{2E}{}^{e} \\ \dots & \dots & 0 & \dots & \dots & \dots \\ b_{e1}{}^{e} & b_{e2}{}^{e} & \dots & 0 & \dots & b_{eE}{}^{e} \\ \dots & \dots & \dots & \dots & 0 & \dots \\ b_{E1}{}^{e} & b_{E2}{}^{e} & 0 & b_{Ee}{}^{e} & \dots & 0 \end{bmatrix} \end{array}
\end{array}\right] \tag{15}$$

$$, v = 1, \dots V, e = 1, \dots, E$$

where

$$\begin{cases} \forall i = 1, \dots, V \ and \ \forall j = 1, \dots, E, \ I_{jv}, \alpha_{iv} \ \epsilon \mathbb{R} \\ \forall i = 1, \dots, V \ and \ \forall j = 1, \dots, E, \ b_{ie}{}^{v}, b_{je}{}^{e} \epsilon \{0,1\} \end{cases}.$$

According to Equation (15), the R. Graph matrix consists of four distinct submatrices, which represent the influences of variable risks on other variables, the influences of variable risks on events, the influences of event risks on variables, and the influences of event risks on other events. Furthermore, in the above equation, α_{iv} represents the risk of variable v due to a 100% risk in variable i. As the R. Graph is non-cyclic, if α_{iv} takes a value, then $\alpha_{vi} = 0$.
Additionally, I_{jv}represents the risk to variable v caused by the occurrence of event j. In the above equations, $b_{je}{}^{e}$ denotes the likelihood of event e occurring due to event j, while $b_{ie}{}^{v}$indicates the likelihood of event e occurring due to variable V_i. If $b_{je}{}^{e}$and $b_{ie}{}^{v}$ take the value of one, it indicates the susceptibility of event e occurring due to event j and the variable i. If they are zero, it indicates non-susceptibility. Here, as the R. Graph is non-cyclic, if $b_{je}{}^{e}$=1 and $b_{ie}{}^{v}$ =1, we will have $b_{ej}{}^{e}$=0 and $b_{ei}{}^{v}$=0.

Definition 3. Consider a set of $\acute{V}$ variables and $\acute{E}$ events that influence a specific variable V_v, where $i = 1, \dots, \acute{V}, j = 1, \dots, \acute{E},$. If the objective is to analyze the rate of change (risk) of the variable V_v with respect to all these factors, under the assumption that all factors are independent, the following expression holds [14]:

$$R(V_v) = R\big(V_v | Par(V_v)\big) = \sum_{i=1}^{\acute{V}} \alpha_{iv} R(V_i) + \sum_{j=1}^{\acute{E}} I_{jv} \tag{12}$$

Here, $Par(V_v)$ denotes all the parent variables of V_v, $R(V_i)$ represents the risk associated with the i −th variable, and $R\big(V_v | Par(V_v)\big)$ refers to the rate of change (or risk) resulting from alterations or occurrences in the parents of V_v.

Definition 4. The risk associated with variable V_v according to the desired event V_i, can be defined in the following manner [14]:

$$\begin{cases} R(V_v|V_i) = \alpha_{iv} R(V_i) + \sum_{l=1}^{L} \alpha_{lv} R(V_l|V_i) + \ \sum_{k=1}^{K} I_{kv} & V_i \epsilon Par(V_v) \\ R(V_v|V_i) = \sum_{l=1}^{L} \alpha_{lv} R(V_l|V_i) + \ \sum_{k=1}^{K} I_{kv} & V_i \notin Par(V_v) \end{cases} \tag{13}$$

where V_l denotes the variables that are either directly or indirectly influenced by V_i;V_i represents the impact of events on V_v, which are the parent variables of V_v, and V_i influences their occurrence. Therefore, based on Equation (16), we can derive the following:

Definition 5. The risk of the variable V_v can be defined according to the desired event E_j, i.e., $R\big(V_v | E_j\big)$ as follows:

$$\begin{cases} R(V_v|E_j) = I_{jv} + \sum_{k=1}^{K} I_{kv} + \sum_{l=1}^{L} \alpha_{lv} R(V_l|E_j) & E_j \epsilon Par(V_v) \\ R(V_v|E_j) = \sum_{k=1}^{K} I_{kv} + \sum_{l=1}^{L} \alpha_{lv} R(V_l|E_j) & E_j \notin Par(V_v) \end{cases} \tag{14}$$

In this relation, I_{kv} represents the influence of events on V_v, which acts as the parent of V_v, and also demonstrates how E_j impacts their occurrences. Additionally, V_l refers to variables that are directly or indirectly influenced by E_j.

Definition 6. In the R.Graph method, the relative significance of each variable is determined as follows [14]:

$$\left\{ {w_i}^v = \frac{\sum_{v=1}^{V} |R(V_v|V_i)| + |R(V_i)|}{\sum_{i=1}^{V} \sum_{v=1}^{V} (|R(V_v|V_i)| + |R(V_i)|) + \sum_{j=1}^{E} \sum_{v=1}^{V} |R(V_v|E_j)|} \right. \tag{15}$$

In this context, ${w_i}^v$ represents the relative significance of each variable, which is calculated based on its own risk value and its influence on the risks of other variables.

4. Proposed R.Graph-Enhanced EDAS Model for Selecting the Best Human-Centric GAI Transformer Model

In this section, we present a comprehensive framework that integrates the R.Graph and Enhanced EDAS methodologies to select the most suitable human-centric GAI Transformer model for supply chain risk management. The proposed model addresses the complexities involved in evaluating and choosing the optimal AI tool by considering multiple criteria pertinent to supply chain risk management. By leveraging the strengths of R.Graph for modeling interactions between criteria and Enhanced EDAS for multi-criteria decision-making, this approach ensures a rigorous and systematic selection process. The framework is designed to improve the effectiveness of AI deployment in managing supply chain risks, ensuring that the chosen model aligns with both operational goals and human-centric considerations.

Step 1: *Formation of Decision and Interaction Matrices with Criteria Weighting*

In the first step, a decision matrix is created, representing the GAI alternatives evaluated against selected criteria. This matrix forms the basis for the decision-making process by capturing the performance of each GAI model. Additionally, an interaction matrix, denoted as $C - C$ and corresponding to the $V - V$ matrix in the R.Graph method, is developed to account for the interdependencies between criteria (see Appendix B for a sample). Once these matrices are established, subjective weights for each criterion are assigned by decision-makers, reflecting the importance of each criterion in the specific supply chain context. These elements collectively provide a robust foundation for evaluating and selecting the most suitable GAI model.

$$c_1 \quad c_1 \quad \cdots \quad c_n \tag{16}$$

$$X = \begin{array}{c} a_1 \\ a_2 \\ \vdots \\ a_m \end{array} \begin{pmatrix} x_{11} & x_{12} & \dots & x_{1n} \\ x_{21} & x_{22} & \dots & x_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ x_{m1} & x_{m2} & \dots & x_{mn} \end{pmatrix}$$

$$C - C = \begin{array}{c} \\ \boldsymbol{C_1} \\ \boldsymbol{C_2} \\ \dots \\ \boldsymbol{C_j} \\ \dots \\ \boldsymbol{C_n} \end{array} \begin{array}{c} \begin{array}{cccccc} \boldsymbol{C_1} & \boldsymbol{C_2} & \dots & \boldsymbol{C_j} & \dots & \boldsymbol{C_n} \end{array} \\ \begin{bmatrix} 0 & \alpha_{12} & \dots & \alpha_{1v} & \dots & \alpha_{1n} \\ \alpha_{21} & 0 & \dots & \alpha_{2v} & \dots & \alpha_{2n} \\ \dots & \dots & 0 & \dots & \dots & \dots \\ \alpha_{j1} & \alpha_{j2} & \dots & 0 & \dots & \alpha_{jn} \\ \dots & 0 & \dots & \dots & 0 & \dots \\ \alpha_{n1} & \alpha_{n2} & 0 & \alpha_{nj} & \dots & 0 \end{bmatrix} \end{array} \tag{17}$$

$$W = [w_{js}]_{1\times n} \tag{18}$$

where X is the decision matrix, representing the evaluation of m alternatives with respect to n criteria, $C - C$ is the interaction matrix between criteria, and α_{jn} denotes the impact of the j-th attribute on the n-th criterion based on a 100% change in Attribute j. W is the subjective weight matrix, where w_{js} denotes the subjective weight of the j-th attribute.

Step 2: *Computing the Mean Values of Each Criterion*

In the second step, we calculate the mean value for each criterion across all alternatives. This step helps us to understand the average performance of each criterion, which will be used as a reference point in subsequent calculations. The mean value of the j-th criterion is calculated using the formula:

$$mean_j = \frac{1}{m}\sum_{i=1}^{m} x_{ij} \tag{19}$$

where $mean_j$ is the average value of the j-th criterion, x_{ij} denotes the performance value of the i-th alternative for the j-th criterion, and m is the total number of alternatives

Step 3: *Calculating the Relative Utilities and Losses*

In the third step, we calculate the relative utilities and losses for each alternative with respect to the mean values computed in Step 2. This step helps to determine how each alternative performs relative to the average performance of each criterion. We consider both beneficial and non-beneficial criteria in these calculations. Beneficial criteria are those for which higher values are better, while non-beneficial criteria are those for which lower values are better.

For beneficial criteria, the relative utilities and losses are calculated using the following formulas:

$$\begin{cases} u_{ij}^{S} = \max\left(0, \frac{x_{ij} - mean_j}{mean_j}\right) \\ l_{ij}^{S} = \max\left(0, -\frac{x_{ij} - mean_j}{mean_j}\right) \end{cases} \tag{20}$$

For non-beneficial criteria, the relative utilities and losses are calculated using these formulas:

$$\begin{cases} u_{ij}^{S} = \max\left(0, \frac{mean_j - x_{ij}}{mean_j}\right) \\ l_{ij}^{S} = \max\left(0, -\frac{mean_j - x_{ij}}{mean_j}\right) \end{cases} \tag{21}$$

where u_{ij}^{S} denotes the relative utility of the i-th alternative for the j-th criterion, and l_{ij}^{S} represents the relative loss of the i-th alternative for the j-th criterion. By using these formulas, we can assess how each alternative performs in comparison to the mean performance for each criterion, taking into account whether the criterion is beneficial or non-beneficial.

Step 4: *Mean of Utilities and Losses Calculations*

In the fourth step, we calculate the mean values for both utilities and losses. This step helps us to understand the distribution of utilities and losses around the performance values of each alternative. The formulas for calculating the mean values for utilities and losses are:

$$\begin{cases} u_{j}^{S} = \frac{\sum_{k=1}^{m} u_{kj}^{S} \cdot I\left(u_{ij}^{S} > 0\right)}{\sum_{k=1}^{m} I\left(u_{ij}^{S} > 0\right)} \\ l_{j}^{S} = \frac{\sum_{k=1}^{m} l_{kj}^{S} \cdot I\left(l_{ij}^{S} > 0\right)}{\sum_{k=1}^{m} I\left(l_{ij}^{S} > 0\right)} \end{cases} \tag{22}$$

where u_{j}^{S} represents the mean of utility values for the j-th criterion, and l_{j}^{S}represents the mean of loss values for the j-th criterion. By calculating these mean values, we gain a clearer understanding of how each alternative's performance compares to the distribution of performance values across each criterion.

Step 5: *Calculating Relative Utilities and Losses Using Mean Values*

In the fifth step, we calculate the relative utilities and losses using the mean values obtained in Step 4. This step further refines the evaluation of each alternative's performance by comparing it to the calculated mean values. This comparison offers insights into how each alternative ranks in relation to others, considering both higher and lower performance values. For beneficial criteria, the relative utilities and losses are calculated using the mean values as follows:

$$\begin{cases} u_{ij}^{S,above} = \max\left(0, \frac{u_{ij}^{S} - u_{j}^{S}}{u_{j}^{S} + 1}\right) \\ u_{ij}^{S,below} = \max\left(0, \frac{u_{j}^{S} - u_{ij}^{S}}{u_{j}^{S} + 1}\right) \\ l_{ij}^{S,above} = \max\left(0, \frac{l_{ij}^{S} - l_{j}^{S}}{1 - l_{j}^{S}}\right) \\ l_{ij}^{S,below} = \max\left(0, \frac{l_{j}^{S} - l_{ij}^{S}}{1 - l_{j}^{S}}\right) \end{cases} \tag{23}$$

For non-beneficial criteria, the relative utilities and losses using mean values are calculated as:

$$\begin{cases} u_{ij}^{S,below} = \max\left(0, \frac{u_{ij}^S - u_j^S}{1-u_j^S}\right) \\ u_{ij}^{S,above} = \max\left(0, \frac{u_j^S - u_{ij}^S}{1-u_j^S}\right) \\ l_{ij}^{S,below} = \max\left(0, \frac{l_{ij}^S - l_j^S}{l_j^S + 1}\right) \\ l_{ij}^{S,above} = \max\left(0, \frac{l_j^S - l_{ij}^S}{l_j^S + 1}\right) \end{cases} \tag{24}$$

where $u_{ij}^{S,below}$ represents the below-average utility performance value for each alternative, based on the mean utility value for the j-th criterion, and $u_{ij}^{S,above}$ represents the above-average utility performance value for each alternative, based on the same mean. Similarly, $l_{ij}^{S,below}$ denotes the below-average loss performance value for each alternative, using the mean loss value for the j-th criterion, and $l_{ij}^{S,above}$ indicates the above-average performance value using the mean loss value for the j-th criterion. By applying these formulas, we enhance the evaluation of each alternative's performance, providing a more precise understanding of how each alternative ranks compared to others, in terms of both better and worse performance values.

Step 6: *Calculating the weights of the criteria considering the interactions using R.Graph*

Using the R.Graph method, where the total number of criteria is represented by n, the relative importance of each attribute is determined by analyzing its impact on the other criteria within the system. This approach considers both the direct and indirect effects that each criterion has on the overall decision-making process. The subjective weights provided by decision-makers are then incorporated into this analysis, allowing for a more nuanced understanding of each criterion's significance. The final relative importance of each attribute is calculated using Eq. (25), which integrates these interactions and subjective weights to provide a comprehensive assessment of the criteria's influence.

$$w_j = \frac{w_{js}(\sum_{v=1}^{n} |R(C_v|C_j)| + |R(C_j)|)}{\sum_{j=1}^{n} w_{js}(\sum_{v=1}^{n} |R(C_v|C_j)| + |R(C_j)|)} \tag{25}$$

where w_j is the final weight of Attribute j considering w_{js} (the subjective weight of Attribute j), and interdependencies between all criteria, $R(C_v|C_j)$ represents the effect on Criterion v due to Criterion j, and $R(C_j)$ denotes the total effect on Criterion j. Accordingly, we have:

$$|R(C_j)| = 1 + \left|R\left(C_j|Par(C_j)\right)\right| = 1 + \sum_{i=1}^{n} \alpha_{ij} R(C_i) \tag{26}$$

$$\begin{cases} R(C_v|C_j) = \alpha_{jv} R(C_j) + \sum_{l=1}^{n} \alpha_{lj} R(C_l|C_j) + 1 & C_i\ directltly\ affcets\ C_v \\ |R(C_v|C_j)| = \sum_{l=1}^{n} \alpha_{lj} R(C_l|C_j) + 1 & C_i\ indirectltly\ affcets\ C_v \end{cases} \tag{27}$$

Derivation: *Eqs. (25) and (26) are derived from Eqs. (12) and (13). It is important to note that since we only consider the effects of criteria on other criteria, to align with the R.Graph-Enhanced method, we assume that the effects of occurrences are a constant value for all criteria and equal to one. This ensures that no weight ends up being zero.*

Step 7*:* *Summarizing the Weighted Values*

In this step, we summarize the weighted values calculated for each alternative. This involves summing the weighted values for utilities and losses across all criteria. The summarized weighted values give an overall picture of the performance of each alternative, taking into account the contributions of all criteria.

The formulas for summarizing the weighted utility values are:

$$\begin{cases} u_{i,weighted} = \sum_j u_{ij}^{S}.w_j \\ u_{i,below,weighted} = \sum_j u_{ij}^{S,below}.w_j \\ u_{i,above,weighted} = \sum_j u_{ij}^{S,above}.w_j \end{cases} \tag{28}$$

Similarly, the formulas for summarizing the weighted values for losses are:

$$\begin{cases} l_{i,weighted} = \sum_j l_{ij}^{S}.w_j \\ l_{i,below,weighted} = \sum_j l_{ij}^{S,below}.w_j \\ l_{i,above,weighted} = \sum_j l_{ij}^{S,above}.w_j \end{cases} \tag{29}$$

where $u_{i,weighted}$ is the total weighted utility of the i-th alternative, $u_{i,below,weighted}$ is the total weighted below-average utility using the mean utility values for the i-th alternative, and $u_{i,above,weighted}$ is the total weighted above-average utility based on the mean utility values for the i-th alternative. Similarly, $l_{i,weighted}$ represents the total weighted loss of the i-th alternative, $l_{i,below,weighted}$ is the total weighted below-average loss using the mean loss values for the i-th alternative, and $l_{i,above,weighted}$ is the total weighted above-average loss using the mean loss values for the i-th alternative. By summarizing these weighted values, we obtain an overall measure of the utility and loss for each alternative, taking into account the weights assigned to the criteria. These summarized values will be used in the next steps to calculate the total utility, total loss, and the final appraisal score for each alternative.

Step 8: *Calculating the Total Utility, Total Loss, and Appraisal Score of Each Alternative*

In this step, we calculate the total utility, total loss, and appraisal score for each alternative. These calculations combine the summarized weighted values from Step 7 to provide a comprehensive evaluation of each alternative's performance. The formulas for calculating the total utility and total loss are:

$$u_i = \frac{\frac{u_{i,weighted}}{\max u_{i,weighted}} + \frac{u_{i,above,weighted}}{\max u_{i,above,weighted}}}{\frac{u_{i,weighted}}{\max u_{i,weighted}} + \frac{u_{i,below,weighted}}{\max u_{i,below,weighted}} + \frac{u_{i,above,weighted}}{\max u_{i,above,weighted}}} \tag{30}$$

$$l_i = \frac{\frac{l_{i,weighted}}{\max l_{i,weighted}} + \frac{l_{i,above,weighted}}{\max l_{i,above,weighted}}}{\frac{l_{i,weighted}}{\max l_{i,weighted}} + \frac{l_{i,below,weighted}}{\max l_{i,below,weighted}} + \frac{l_{i,above,weighted}}{\max l_{i,above,weighted}}} \tag{31}$$

where u_i is the total utility of the i-th alternative, and l_i is the total loss of the i-th alternative.

Step 9: *Calculating the Appraisal Score (AS)*

Finally, the appraisal score AS_i is calculated using the total utility and total loss:

$$AS_i = \frac{1}{2}\left(\frac{u_i}{max_i(u_i)} + 1 - \frac{l_i}{max_i(l_i)}\right) \tag{32}$$

where AS_i is the appraisal score of the i-th alternative. The appraisal score AS_i provides a comprehensive measure of each alternative's performance by considering both the total utility and total loss. The higher the appraisal score, the better the performance of the alternative. This score is used in the next step to rank the alternatives.

Now, the alternatives are ranked based on their appraisal scores in descending order. The flowchart of the proposed model is depicted in Fig. 4 and Algorithm 1.

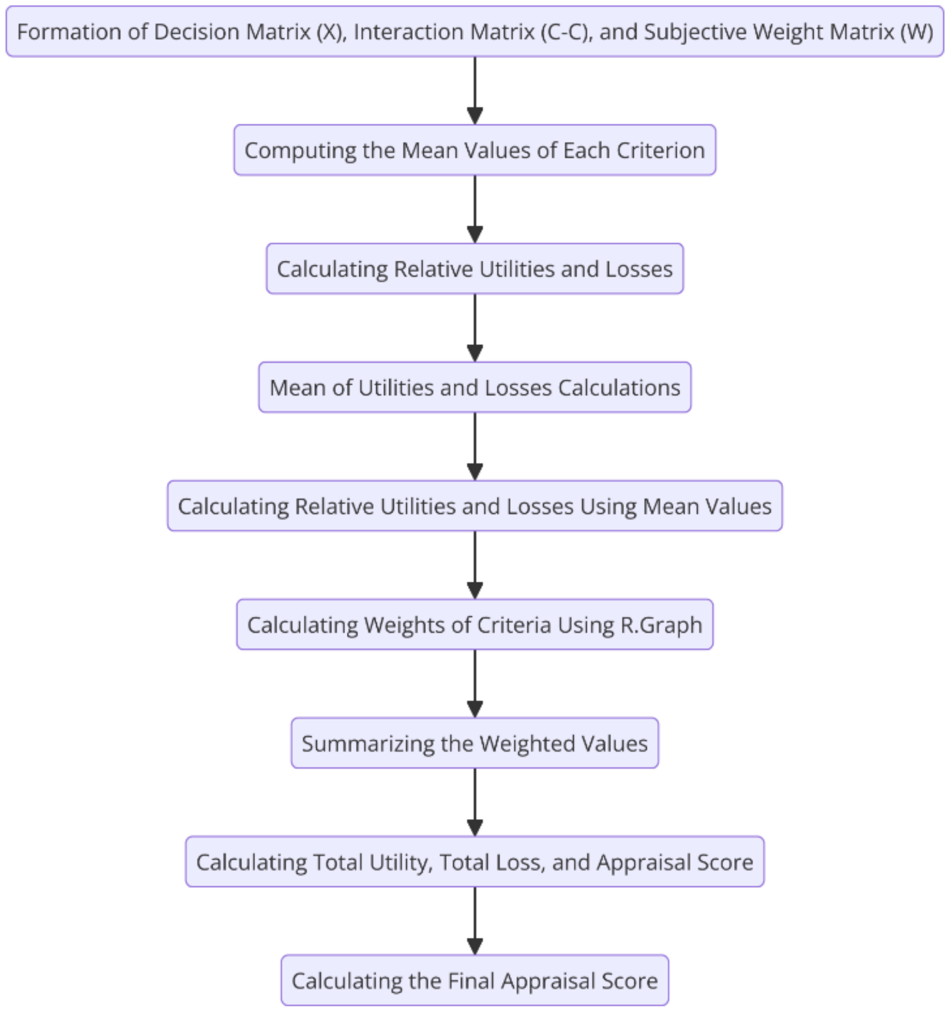


Figure 3. Flowchart of the proposed model

Algorithm 1: R.Graph-Enhanced method

Input: Decision matrix (X), Interaction matrix ($C - C$) and subjective weight matrix (W)
Output: Ranked alternatives

Step 1: Formation of Decision (X), and Interaction Matrices ($C - C$) with Criteria Weighting (W)

Step 2: Computing the Mean Values of Each Criterion

$$mean_j = \frac{1}{m}\sum_{i=1}^{m} x_{ij}$$

Step 3: Calculating the Relative Utilities and Losses of each option in j-th attribute:

For beneficial criteria: $\begin{cases} u_{ij}^S = \max\left(0, \frac{x_{ij}-mean_j}{mean_j}\right) \\ l_{ij}^S = \max\left(0, -\frac{x_{ij}-mean_j}{mean_j}\right) \end{cases}$, For non-beneficial criteria: $\begin{cases} u_{ij}^S = \max\left(0, \frac{mean_j-x_{ij}}{mean_j}\right) \\ l_{ij}^S = \max\left(0, -\frac{mean_j-x_{ij}}{mean_j}\right) \end{cases}$

Step 4: Mean of Utilities and Losses Calculations of Each Attribute

$$\begin{cases} u_j^S = \frac{\sum_{k=1}^{m} u_{kj}^S \,.\, I\left(u_{ij}^S > 0\right)}{\sum_{k=1}^{m} I\left(u_{ij}^S > 0\right)} \\ l_j^S = \frac{\sum_{k=1}^{m} l_{kj}^S \,.\, I\left(l_{ij}^S > 0\right)}{\sum_{k=1}^{m} I\left(l_{ij}^S > 0\right)} \end{cases}$$

Step 5: Calculating Relative Utilities and Losses Using Mean Values

For beneficial criteria:: $\begin{cases} u_{ij}^{S,above} = \max\left(0, \frac{u_{ij}^{S} - u_{j}^{S}}{u_{j}^{S}+1}\right) \\ u_{ij}^{S,below} = \max\left(0, \frac{u_{j}^{S} - u_{ij}^{S}}{u_{j}^{S}+1}\right) \\ l_{ij}^{S,above} = \max\left(0, \frac{l_{ij}^{S} - l_{j}^{S}}{1-l_{j}^{S}}\right) \\ l_{ij}^{S,below} = \max\left(0, \frac{l_{j}^{S} - l_{ij}^{S}}{1-l_{j}^{S}}\right) \end{cases}$ For non-beneficial criteria: $\begin{cases} u_{ij}^{S,below} = \max\left(0, \frac{u_{ij}^{S} - u_{j}^{S}}{1-u_{j}^{S}}\right) \\ u_{ij}^{S,above} = \max\left(0, \frac{u_{j}^{S} - u_{ij}^{S}}{1-u_{j}^{S}}\right) \\ l_{ij}^{S,below} = \max\left(0, \frac{l_{ij}^{S} - l_{j}^{S}}{l_{j}^{S}+1}\right) \\ l_{ij}^{S,above} = \max\left(0, \frac{l_{j}^{S} - l_{ij}^{S}}{l_{j}^{S}+1}\right) \end{cases}$

Step 6: Calculating the weights of the criteria considering the interactions using R.Graph

$$w_j = \frac{w_{js}\left(\sum_{v=1}^{n} |R(C_v|C_j)| + |R(C_j)|\right)}{\sum_{j=1}^{n} w_{js}\left(\sum_{v=1}^{n} |R(C_v|C_j)| + |R(C_j)|\right)}$$

where:

$$|R(C_j)| = 1 + \left|R\left(C_j|Par(C_j)\right)\right| = 1 + \sum_{i=1}^{n} \alpha_{ij} R(C_i)$$

$$\begin{cases} R(C_v|C_j) = \alpha_{jv} R(C_j) + \sum_{l=1}^{n} \alpha_{lj} R(C_l|C_j) + 1 & C_i \ directltly \ affcets \ C_v \\ |R(C_v|C_j)| = \sum_{l=1}^{n} \alpha_{lj} R(C_l|C_j) + 1 & C_i \ indirectltly \ affcets \ C_v \end{cases}$$

Step 7: Summarizing the Weighted Values

The weighted utility values: $\begin{cases} u_{i,weighted} = \sum_j u_{ij}^{S}.w_j \\ u_{i,below,weighted} = \sum_j u_{ij}^{S,below}.w_j \\ u_{i,above,weighted} = \sum_j u_{ij}^{S,above}.w_j \end{cases}$

The weighted losses values: $\begin{cases} l_{i,weighted} = \sum_j l_{ij}^{S}.w_j \\ l_{i,below,weighted} = \sum_j l_{ij}^{S,below}.w_j \\ l_{i,above,weighted} = \sum_j l_{ij}^{S,above}.w_j \end{cases}$

Step 8: Calculating the Total Utility, Total Loss, and Appraisal Score of Each Alternative

$$u_i = \frac{\frac{u_{i,weighted}}{\max u_{i,weighted}} + \frac{u_{i,above,weighted}}{\max u_{i,above,weighted}}}{\frac{u_{i,weighted}}{\max u_{i,weighted}} + \frac{u_{i,below,weighted}}{\max u_{i,below,weighted}} + \frac{u_{i,above,weighted}}{\max u_{i,above,weighted}}} \; ; \; l_i = \frac{\frac{l_{i,weighted}}{\max l_{i,weighted}} + \frac{l_{i,above,weighted}}{\max l_{i,above,weighted}}}{\frac{l_{i,weighted}}{\max l_{i,weighted}} + \frac{l_{i,below,weighted}}{\max l_{i,below,weighted}} + \frac{l_{i,above,weighted}}{\max l_{i,above,weighted}}}$$

Step 9: Calculating the Appraisal Score (AS)

$$AS_i = \frac{1}{2}\left(\frac{u_i}{max_i(u_i)} + 1 - \frac{l_i}{max_i(l_i)}\right)$$

5. Case Study

The food industry's supply chain is particularly dynamic and intricate, making it one of the most critical and important supply chains in the global economy. Its efficient functioning has a profound and influential impact on various aspects of society and the economy. Ensuring the smooth operation of this supply chain is essential for maintaining food security, supporting economic stability, safeguarding public health, and promoting environmental sustainability. Disruptions in the food supply chain can lead to significant consequences, highlighting the need for robust management and innovative solutions to mitigate risks and enhance resilience.

The food industry supply chain is a complex system involving multiple stages, each presenting unique challenges and risks. It begins with the procurement of raw materials from various suppliers, often spread across different regions, leading to risks such as supplier delays and natural disasters disrupting supply. The materials then undergo processing and manufacturing, where issues like equipment malfunctions and quality control problems can cause delays or product recalls. Transportation and logistics are crucial but face risks like delays, fuel price fluctuations, and political instability. Finally, the delivery of goods to retailers and consumers involves managing inventory, forecasting demand, and ensuring food safety, while adapting to changing consumer preferences and market trends.

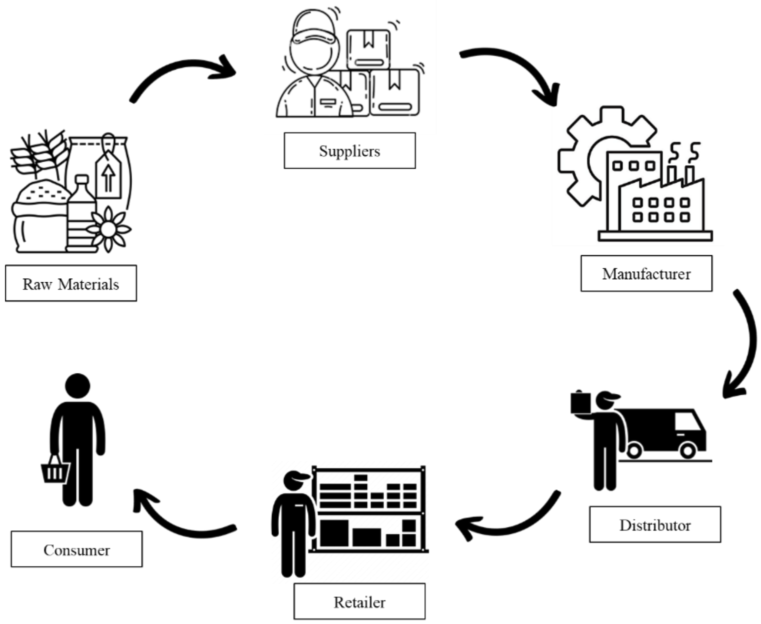
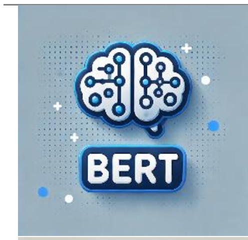
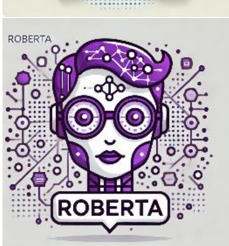


Figure 4.A simplified food industries supply chain system

Risk management in supply chain operations is crucial for ensuring continuity, minimizing losses, and maintaining customer satisfaction. It involves identifying, assessing, and mitigating risks to reduce disruptions and control costs. In today's globalized market, strong risk management is vital for staying competitive and protecting against unexpected events. Strategies include diversifying suppliers, maintaining safety stock, and using advanced technologies for better forecasting. Generative AI (GAI) transformers have emerged as effective tools for analyzing large datasets and identifying risks. This section focuses on using the R.Graph-Enhanced EDAS method to evaluate and rank GAI transformer algorithms for supply chain risk management. In our analysis, we engaged three experts with relevant knowledge of GAI technologies and food supply chain risk management. We utilized interactive methods to define appropriate criteria, alternatives, and develop both a decision matrix and an interaction matrix between the criteria. These collaborative efforts ensured a comprehensive and informed evaluation of GAI transformer algorithms for effective risk management in the food supply chain.

The alternatives considered for evaluating the most efficient NLP transformer algorithm for managing supply chain risks are: BERT (A1), GPT (A2), Transformer-XL (A3), XLNet (A4), RoBERTa (A5), T5 (A6), and DistilBERT (A7). Each of these models offers unique features and capabilities, making them suitable for different aspects of supply chain risk management. To enable a comprehensive comparison, the key characteristics of each alternative are summarized in Table 1 below.

Table 1. Classification of elected NLP transformers algorithms

Alternative	Descriptions
	BERT (A1): BERT (Bidirectional Encoder Representations from Transformers) excels in understanding the context of words in a sentence by looking at both directions. It is widely used for various NLP tasks due to its strong performance in understanding language nuances. BERT is particularly effective in tasks requiring deep understanding of text.
	GPT (A2): GPT (Generative Pre-trained Transformer) is designed for text generation and language modeling tasks. It leverages unsupervised learning to generate coherent and contextually relevant text. GPT's strength lies in its ability to produce high-quality, human-like text based on the input it receives.
	Transformer-XL (A3): Transformer-XL introduces a segment-level recurrence mechanism to capture longer-term dependencies in text. This model is particularly useful for tasks involving long documents or sequences. It provides improved performance on tasks that require understanding of long-range context.
	XLNet (A4): XLNet is a generalized autoregressive pretraining method that combines the advantages of BERT and Transformer-XL. It can capture bidirectional context while also handling long-term dependencies. XLNet outperforms many models in various NLP benchmarks by addressing limitations in previous models.
	RoBERTa (A5): RoBERTa (Robustly optimized BERT approach) is an optimized version of BERT with improved training techniques and more extensive data. It achieves higher performance on many NLP tasks by refining BERT's pretraining process. RoBERTa is known for its robustness and efficiency in text understanding tasks.

T5 (A6): T5 (Text-To-Text Transfer Transformer) treats all NLP tasks as text-to-text problems, making it highly versatile. It can handle a wide range of tasks, from translation to summarization, with a single model architecture. T5's unified approach simplifies the application of the model to various tasks.
DistilBERT (A7): DistilBERT is a distilled version of BERT, designed to be smaller and faster while retaining most of BERT's performance. It offers a more efficient solution for applications with limited computational resources. DistilBERT is ideal for scenarios where speed and resource efficiency are critical.

Table 2 presents the criteria and sub-criteria, along with their respective weights, which were determined by experts in the fields of GAI technologies and supply chain risk management. These criteria have been carefully selected to cover various aspects of performance, reliability, and impact. By assigning weights to each criterion and sub-criterion, we can prioritize the factors that are most crucial for the effective management of supply chain risks using NLP transformer algorithms. This expert-driven, structured approach ensures a comprehensive evaluation, enabling stakeholders to identify the strengths and weaknesses of different algorithms in real-world applications. The decision matrix for this research, presented in Table 3, was also developed by the experts through a thorough interactive and consensus-based process using a questionary (Appendix A). This matrix evaluates the performance of various alternatives according to the carefully selected criteria, serving as a comprehensive tool for assessing the effectiveness, efficiency, adaptability, and overall impact of each NLP transformer algorithm. By systematically comparing each alternative against these weighted criteria, the decision matrix facilitates an objective and data-driven determination of the most suitable algorithm for enhancing supply chain resilience and reliability.

Table 2. Criteria and Sub-Criteria with Weights for Evaluating NLP Transformer Algorithms in Supply Chain Risk Management

Criteria	Weight	Criterion Type	Sub-Criteria	Weight	Description
Effectiveness	0.335	Qualitative	Accuracy of Demand Volatility Predictions (C_1)	0.224	This criterion refers to the precision of forecasts in predicting variations in demand. It measures how well the system can accurately anticipate changes in customer demand patterns within a given time frame.
		Qualitative	Timeliness of Supplier Disruption Alerts (C_2)	0.212	This criterion focuses on the promptness of alerts generated by the system in response to supplier disruptions. It assesses how quickly and efficiently the system can notify relevant stakeholders about potential disruptions in the supply chain.
		Qualitative	Precision in Transportation Delay Forecasts (C_3)	0.200	This criterion gauges the accuracy of forecasts related to transportation delays. It evaluates the system's ability to provide precise estimations of delays that may occur during the transportation of goods, enabling proactive measures to mitigate their impact.
		Quantitative	Detection Rate of Inventory Imbalances (C_4)	0.188	This criterion measures the effectiveness of the system in identifying inventory imbalances, such as excess or insufficient stock levels. It evaluates the system's capability to detect and flag discrepancies between expected and actual inventory quantities.
		Quantitative	Identification Rate of Production Bottlenecks (C_5)	0.176	This criterion assesses how well the system can identify production bottlenecks, which are constraints that limit the overall output of a manufacturing process. It measures the system's ability to pinpoint specific areas where production inefficiencies occur.
Efficiency	0.230	Qualitative	Data Privacy Measures Implemented (C_6)	0.235	This criterion focuses on the measures implemented to ensure data privacy and security. It evaluates the system's adherence to data protection regulations, confidentiality of sensitive information, and the implementation of safeguards to prevent unauthorized access or data breaches.
		Quantitative	Model Training Time and Complexity (C_7)	0.217	This criterion pertains to the time required and the complexity involved in training the system's predictive models. It assesses the efficiency and feasibility of the model training process, considering factors such as computation resources, algorithm complexity, and data preparation.
		Quantitative	Initial Implementation Costs (C_8)	0.200	This criterion measures the upfront costs associated with implementing the system. It includes expenses related to software acquisition, hardware infrastructure, implementation services, and any necessary customization or integration with existing systems.
		Qualitative	Computational Resources Utilization (C_9)	0.183	This criterion evaluates the efficient utilization of computational resources by the system. It assesses factors such as CPU, memory, and storage usage, and how effectively the system optimizes resource allocation to ensure smooth and reliable operations.
		Qualitative	Adherence to Regulatory Standards (C_{10})	0.165	This criterion focuses on the system's compliance with relevant regulatory standards and industry-specific requirements. It assesses whether the system meets the necessary legal and industry-specific guidelines, ensuring data privacy, security, and ethical data usage.
Adaptability	0.125	Qualitative	Frequency of Real-time Updates	0.264	This criterion measures the frequency at which the system provides real-time updates and

Criteria	Weight	Criterion Type	Sub-Criteria	Weight	Description
			(C_{11})		information. It assesses how quickly the system can capture and relay relevant data, enabling stakeholders to make timely decisions based on the most current information available.
		Qualitative	Tailored Solutions for Industry Specifics (C_{12})	0.232	This criterion evaluates the system's ability to provide customized solutions that address specific requirements and challenges within a particular industry. It assesses whether the system can adapt and accommodate industry-specific nuances and optimize its functionality accordingly.
		Qualitative	Scalability with Data Volume Increases (C_{13})	0.200	This criterion measures the system's scalability in handling and processing larger volumes of data. It assesses whether the system can effectively scale up its computational capabilities and accommodate increasing data loads without compromising performance or efficiency.
		Qualitative	Compatibility with Existing IT Infrastructure (C_{14})	0.168	This criterion evaluates the compatibility of the system with the organization's existing IT infrastructure. It assesses whether the system can seamlessly integrate with the organization's current software, hardware, and data architecture, minimizing disruptions and maximizing efficiency.
		Qualitative	Ease of Model Version Control (C_{15})	0.136	This criterion assesses the ease of managing and controlling different versions of the system's predictive models. It evaluates whether the system provides efficient mechanisms for tracking, updating, and deploying new versions of models while ensuring consistency and reliability.
Impact	0.310	Quantitative	Percentage Reduction in Disruptions (C_{16})	0.271	This criterion measures the effectiveness of the system in reducing disruptions within the supply chain. It evaluates the system's impact by quantifying the percentage decrease in the occurrence of disruptions, such as delays, stockouts, or quality issues.
		Quantitative	Cost Reduction in Risk Management (C_{17})	0.242	This criterion focuses on the system's ability to reduce costs associated with risk management activities. It assesses whether the implementation of the system leads to tangible cost savings by minimizing the occurrence and impact of supply chain risks.
		Qualitative	Improvement in Decision-making Speed (C_{18})	0.216	This criterion measures the system's impact on enhancing decision-making speed within the supply chain. It evaluates whether the system provides timely and accurate information that enables stakeholders to make faster and more informed decisions.
		Qualitative	Efficiency Gains in Communication (C_{19})	0.165	This criterion assesses the efficiency gains achieved in communication processes within the supply chain. It measures whether the system facilitates smoother and more effective communication among stakeholders, reducing delays, misunderstandings, and errors.
		Qualitative	Energy-Efficient Model Design (C_{20})	0.106	This criterion focuses on the energy efficiency of the system's model design. It assesses whether the system's algorithms and computational processes are optimized to minimize energy consumption, contributing to sustainable and environmentally-friendly operations.

Table 3. Decision Matrix Evaluating the Performance of NLP Transformer Algorithms

Criteria	Sub-Criteria	Unit	BERT (A_1)	GPT (A_2)	Transformer-XL (A_3)	XLNet (A_4)	RoBERTa (A_5)	T5 (A_6)	DistilBERT (A_7)
Effectiveness	Accuracy of Demand Volatility Predictions (C_1)	-	H	VH	M	H	VH	H	M
	Timeliness of Supplier Disruption Alerts (C_2)	-	M	H	H	VH	H	VH	M
	Precision in Transportation Delay Forecasts (C_3)	-	H	VH	H	H	H	VH	M
	Detection Rate of Inventory Imbalances (C_4)	Percentage (%)	85%	90%	80%	90%	85%	85%	80%
	Identification Rate of Production Bottlenecks (C_5)	Percentage (%)	80%	85%	75%	85%	85%	80%	80%
Efficiency	Data Privacy Measures Implemented (C_6)	-	H	VH	H	H	VH	VH	H
	Model Training Time and Complexity (C_7)	Time (Minutes)	120	180	150	160	130	200	90
	Initial Implementation Costs (C_8)	Currency ($)	$10000	$15000	$12000	$13000	$11000	$14000	$9000
	Computational Resources Utilization (C_9)	-	M	L	M	M	H	L	H
	Adherence to Regulatory Standards (C_{10})	-	H	VH	H	H	VH	VH	H
Adaptability	Frequency of Real-time Updates (C_{11})	-	H	VH	H	VH	VH	VH	H
	Tailored Solutions for Industry Specifics (C_{12})	-	M	H	M	H	H	VH	M
	Scalability with Data Volume Increases (C_{13})	-	H	VH	H	H	VH	VH	H
	Compatibility with Existing IT Infrastructure (C_{14})	-	VH	VH	H	H	VH	VH	H
	Ease of Model Version Control (C_{15})	-	VH	VH	H	H	VH	VH	H
Impact	Percentage Reduction in Disruptions (C_{16})	Percentage (%)	75%	85%	70%	80%	85%	80%	75%
	Cost Reduction in Risk Management (C_{17})	Currency ($)	$12000	$15000	$11000	$13000	$14000	$12500	$11500
	Improvement in Decision-making Speed (C_{18})	-	H	VH	M	H	VH	VH	H
	Efficiency Gains in Communication (C_{19})	-	H	VH	H	VH	VH	VH	H

Criteria	Sub-Criteria	Unit	BERT (A_1)	GPT (A_2)	Transformer-XL (A_3)	XLNet (A_4)	RoBERTa (A_5)	T5 (A_6)	DistilBERT (A_7)
	Energy-Efficient Model Design (C_{20})	-	H	M	H	M	VH	L	VH

The decision matrix provides a linguistic assessment of each algorithm's effectiveness, efficiency, adaptability, and impact, enabling a clear comparison to identify the most suitable option for supply chain risk management. The quantified decision matrix related to this paper is presented in Table 4. This matrix provides a numerical evaluation of the performance of various NLP transformer algorithms against the identified criteria and sub-criteria.

Table 4. The Quantified Decision Matrix Evaluating the Performance of NLP Transformer Algorithms

Criteria	Sub-Criteria	Unit	BERT (A_1)	GPT (A_2)	Transformer-XL (A_3)	XLNet (A_4)	RoBERTa (A_5)	T5 (A_6)	DistilBERT (A_7)
Effectiveness	Accuracy of Demand Volatility Predictions (C_1)	-	4	5	3	4	5	4	3
	Timeliness of Supplier Disruption Alerts (C_2)	-	3	4	4	5	4	5	3
	Precision in Transportation Delay Forecasts (C_3)	-	4	5	4	4	4	5	3
	Detection Rate of Inventory Imbalances (C_4)	Percentage (%)	85%	90%	80%	90%	85%	85%	80%
	Identification Rate of Production Bottlenecks (C_5)	Percentage (%)	80%	85%	75%	85%	85%	80%	80%
Efficiency	Data Privacy Measures Implemented (C_6)	-	4	5	4	4	5	5	4
	Model Training Time and Complexity (C_7)	Time (Minutes)	120	180	150	160	130	200	90
	Initial Implementation Costs (C_8)	Currency ($)	$10000	$15000	$12000	$13000	$11000	$14000	$9000
	Computational Resources Utilization (C_9)	-	3	2	3	3	4	2	4
	Adherence to Regulatory Standards (C_{10})	-	4	5	4	4	5	5	4
Adaptability	Frequency of Real-time Updates (C_{11})	-	4	5	4	5	5	5	4
	Tailored Solutions for Industry Specifics (C_{12})	-	3	4	3	4	4	5	3

	Scalability with Data Volume Increases (C_{13})	-	4	5	4	4	5	5	4
	Compatibility with Existing IT Infrastructure (C_{14})	-	5	5	4	4	5	5	4
	Ease of Model Version Control (C_{15})	-	5	5	4	4	5	5	4
Impact	Percentage Reduction in Disruptions (C_{16})	Percentage (%)	75%	85%	70%	80%	85%	80%	75%
	Cost Reduction in Risk Management (C_{17})	Currency ($)	$12000	$15000	$11000	$13000	$14000	$12500	$11500
	Improvement in Decision-making Speed (C_{18})	-	4	5	3	4	5	5	4
	Efficiency Gains in Communication (C_{19})	-	4	5	4	5	5	5	4
	Energy-Efficient Model Design (C_{20})	-	4	3	4	3	5	2	5

To recognize the relationships between the criteria, we conducted a questionnaire among experts (Appendix B). This questionnaire aimed to assess the impacts and interdependencies between different criteria by requesting experts to provide percentage changes or numerical values based on specific scenarios. By doing so, we gained insights into how changes in one criterion might affect others, allowing us to map out the intricate relationships within our decision matrix. The results of this questionnaire are depicted in the next graph and matrix. These visual representations illustrate the strength and direction of the relationships between the various criteria, helping to identify which factors are most influential in the context of supply chain risk management. The detailed analysis provides a clearer understanding of how improving one aspect, such as the accuracy of demand volatility predictions, can lead to improvements in related areas like cost reduction and decision-making speed. This interconnected view is crucial for developing comprehensive strategies to enhance the overall efficiency and resilience of supply chains.

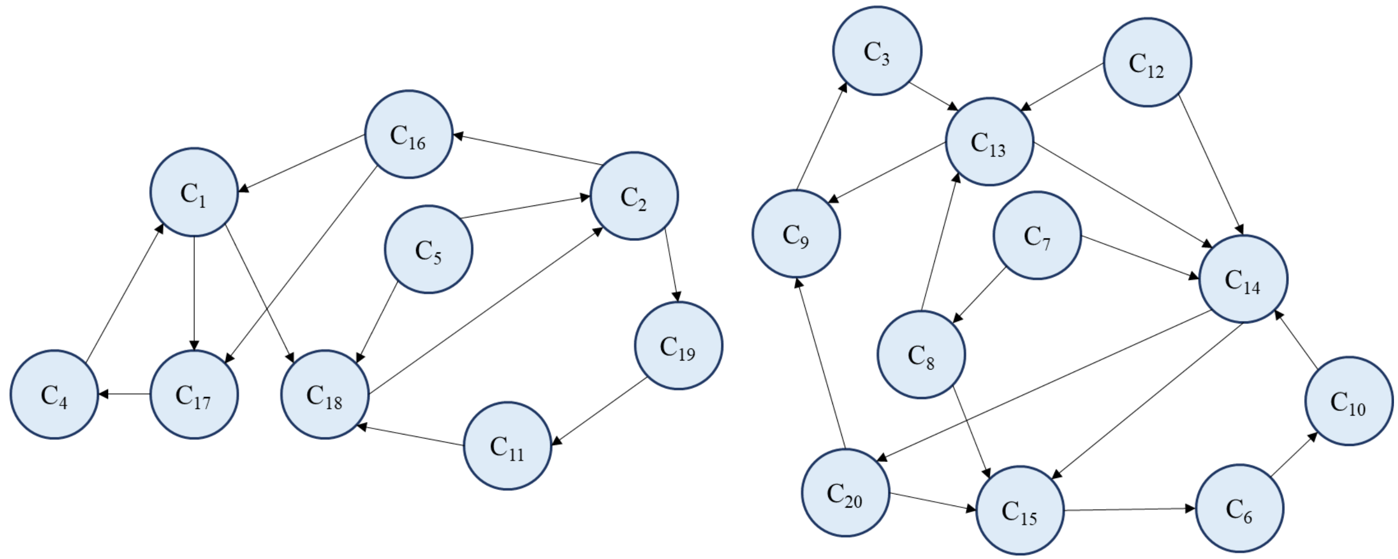


Figure 5. Chain of factors and their impact in supply chain risk management

Table 5. Matrix of Factors and Their Impact in Supply Chain Risk Management

Variable	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	C15	C16	C17	C18	C19	C20
C1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.6	0.5	0	0
C2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.4	0	0	0.4	0
C3	0	0	0	0	0	0	0	0	0	0	0	0	0.3	0	0	0	0	0	0	0
C4	0.7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
C5	0	0.6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.4	0	0
C6	0	0	0	0	0	0	0	0	0	0.5	0	0	0	0	0	0	0	0	0	0
C7	0	0	0	0	0	0	0	0.6	0	0	0	0	0	0.4	0	0	0	0	0	0
C8	0	0	0	0	0	0	0	0	0	0	0	0	-0.3	0	-0.5	0	0	0	0	0
C9	0	0	0.3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
C10	0	0	0	0	0	0	0	0	0	0	0	0	0	0.4	0	0	0	0	0	0
C11	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.4	0	0
C12	0	0	0	0	0	0	0	0	0	0	0	0	0.5	0.4	0	0	0	0	0	0
C13	0	0	0	0	0	0	0	0	0.5	0	0	0	0	0.4	0	0	0	0	0	0

C14	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.5	0	0	0	0	0.4
C15	0	0	0	0	0	0.4	0	0	0	0	0	0	0	0	0	0	0	0	0	0
C16	0.6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.5	0	0	0
C17	0	0	0	0.5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
C18	0	0.4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
C19	0	0	0	0	0	0	0	0	0	0	0.3	0	0	0	0	0	0	0	0	0
C20	0	0	0	0	0	0	0	0	0.4	0	0	0	0	0	0.3	0	0	0	0	0

5.1. Step-by-step analysis of the outputs obtained by the R.Graph enhanced-EDAS method

In this section, we provide a detailed analysis of the results obtained using the R.Graph-Enhanced EDAS method. The analysis includes the calculation of the decision matrix, mean values, relative utilities, and losses, aggregation of these values, and the final ranking of alternatives as follows:

Step 1. *Computing the Mean Values of Each Criterion*

In the first step of the proposed method, we calculate the mean value for each criterion across all alternatives. This mean serves as a baseline, enabling a comparison of how each alternative performs relative to the average. The mean values are then computed using Eq. (19), which provides the necessary foundation for further analysis. These calculated mean values help in identifying whether an alternative's performance is above or below the average for each criterion. The results of these calculations are presented in Table 6.

Table 6. Mean Values for each Criteria

Criteria	Mean Value	Criteria	Mean Value	Criteria	Mean Value	Criteria	Mean Value
C1	4.00	C6	4.42	C11	4.57	C16	78.57
C2	4.00	C7	147.14	C12	3.71	C17	12714.29
C3	4.14	C8	12000	C13	4.42	C18	4.28
C4	85.00	C9	3.00	C14	4.57	C19	4.57
C5	81.42	C10	4.42	C15	4.57	C20	3.71

Step 2. *Calculating the Relative Utilities and Losses*

In the second step, the relative utilities and losses for each alternative are calculated based on the mean values determined in Step 2. The relative utilities and losses are calculated using specific equations—Eq. (20) for beneficial criteria and Eq. (21) for non-beneficial criteria. The results from these calculations are essential for understanding the overall performance of each alternative and are presented in detail in Tables 7 and 8.

Table 7. Related Utilities for each criterion and alternative

	A1	A2	A3	A4	A5	A6	A7
C1	0.000	0.250	0.000	0.000	0.25	0.000	0.000
C2	0.000	0.000	0.000	0.25	0.000	0.25	0.000
C3	0.000	0.206	0.000	0.000	0.000	0.206	0.000
C4	0.000	0.058	0.000	0.058	0.000	0.000	0.000
C5	0.000	0.043	0.000	0.043	0.043	0.000	0.000
C6	0.000	0.129	0.000	0.000	0.129	0.129	0.000
C7	0.184	0.000	0.000	0.000	0.116	0.000	0.388
C8	0.166	0.000	0.000	0.000	0.083	0.000	0.250
C9	0.000	0.333	0.000	0.000	0.000	0.333	0.000
C10	0.000	0.129	0.000	0.000	0.129	0.129	0.000

	A1	A2	A3	A4	A5	A6	A7
C11	0.000	0.093	0.000	0.093	0.093	0.093	0.000
C12	0.000	0.076	0.000	0.076	0.076	0.346	0.000
C13	0.000	0.129	0.000	0.000	0.129	0.1290	0.000
C14	0.093	0.093	0.000	0.000	0.093	0.093	0.000
C15	0.093	0.093	0.000	0.000	0.093	0.093	0.000
C16	0.000	0.081	0.000	0.018	0.081	0.018	0.000
C17	0.000	0.179	0.000	0.022	0.101	0.000	0.000
C18	0.000	0.166	0.000	0.000	0.166	0.166	0.000
C19	0.000	0.093	0.000	0.093	0.093	0.093	0.000
C20	0.076	0.000	0.076	0.000	0.346	0.000	0.3461

Table 8. Relative Losses for each criterion and alternative

	A1	A2	A3	A4	A5	A6	A7
C1	0.000	0.000	0.25	0.000	0.000	0.000	0.250
C2	0.250	0.000	0.000	0.000	0.000	0.000	0.250
C3	0.034	0.000	0.034	0.034	0.034	0.000	0.275
C4	0.000	0.000	0.058	0.000	0.000	0.000	0.058
C5	0.017	0.000	0.078	0.000	0.000	0.017	0.017
C6	0.096	0.000	0.096	0.096	0.000	0.000	0.096
C7	0.000	0.223	0.019	0.087	0.000	0.359	0.000
C8	0.000	0.25	0.000	0.083	0.000	0.166	0.000
C9	0.000	0.000	0.000	0.000	0.333	0.000	0.333
C10	0.096	0.000	0.096	0.096	0.000	0.000	0.096
C11	0.125	0.000	0.125	0.000	0.000	0.000	0.125
C12	0.192	0.000	0.192	0.000	0.000	0.000	0.192
C13	0.096	0.000	0.096	0.096	0.000	0.000	0.096
C14	0.000	0.000	0.125	0.125	0.000	0.000	0.125
C15	0.000	0.000	0.125	0.125	0.000	0.000	0.125
C16	0.045	0.000	0.109	0.000	0.000	0.000	0.045
C17	0.056	0.000	0.134	0.000	0.000	0.016	0.095
C18	0.066	0.000	0.300	0.066	0.000	0.000	0.066
C19	0.125	0.000	0.125	0.000	0.000	0.000	0.125
C20	0.000	0.192	0.000	0.192	0.000	0.461	0.000

Step 3. *Mean Of Utilities and Losses Calculations*

In the third, the mean values for both utilities and losses are calculated across all criteria for each alternative. These mean values are computed using Eq. (22), which provides a standardized method for evaluating the cumulative utility and loss for each alternative. The results of these calculations, which are crucial for the final assessment and ranking of the alternatives, are detailed in Tables 9 and 10.

Table 9. Mean Value for Utilities

Criteria	Mean Utilities	Criteria	Mean Utilities	Criteria	Mean Utilities	Criteria	Mean Utilities
C1	0.250	C6	0.129	C11	0.093	C16	0.05
C2	0.250	C7	0.229	C12	0.144	C17	0.075
C3	0.206	C8	0.166	C13	0.129	C18	0.166
C4	0.058	C9	0.333	C14	0.093	C19	0.093
C5	0.043	C10	0.129	C15	0.093	C20	0.211

Table 10. Mean Value for Losses

Criteria	Mean Losses	Criteria	Mean Losses	Criteria	Mean Losses	Criteria	Mean Losses
C1	0.250	C6	0.096	C11	0.125	C16	0.066
C2	0.250	C7	0.172	C12	0.192	C17	0.101
C3	0.082	C8	0.166	C13	0.096	C18	0.125
C4	0.058	C9	0.333	C14	0.125	C19	0.125
C5	0.032	C10	0.096	C15	0.125	C20	0.282

Step 4. *Mean Above and Mean Below Calculations*

In the fourth step, the mean above and mean below values for both utilities and losses are calculated for each alternative. This step is vital for understanding how the performance of each alternative is distributed relative to the overall set of alternatives. By determining these values, insights are gained into whether an alternative tends to perform above or below the average, which helps in identifying outliers and understanding the relative strengths and weaknesses of each option.

These calculations are performed using Eqs.(23) and (24), allowing for a detailed comparison of each alternative's performance against the overall distribution. The results of this analysis, which are crucial for making informed decisions in the ranking and selection process, are presented in Tables 11 to 14.

Table 11. Mean Above utilities

	A1	A2	A3	A4	A5	A6	A7
C1	0.000	0.000	0.000	0.000	0.000	0.000	0.000
C2	0.000	0.000	0.000	0.000	0.000	0.000	0.000
C3	0.000	0.000	0.000	0.000	0.000	0.000	0.000
C4	0.000	0.000	0.000	0.000	0.000	0.000	0.000
C5	0.000	0.000	0.000	0.000	0.000	0.000	0.000
C6	0.000	0.000	0.000	0.000	0.000	0.000	0.000

C7	0.000	0.000	0.000	0.000	0.000	0.000	0.128
C8	0.000	0.000	0.000	0.000	0.000	0.000	0.071
C9	0.000	0.000	0.000	0.000	0.000	0.000	0.000
C10	0.000	0.000	0.000	0.000	0.000	0.000	0.000
C11	0.000	0.000	0.000	0.000	0.000	0.000	0.000
C12	0.000	0.000	0.000	0.000	0.000	0.176	0.000
C13	0.000	0.000	0.000	0.000	0.000	0.000	0.000
C14	0.000	0.000	0.000	0.000	0.000	0.000	0.000
C15	0.000	0.000	0.000	0.000	0.000	0.000	0.000
C16	0.000	0.030	0.000	0.000	0.030	0.000	0.000
C17	0.000	0.000	0.054	0.000	0.000	0.000	0.018
C18	0.000	0.000	0.000	0.000	0.000	0.000	0.000
C19	0.000	0.000	0.000	0.000	0.000	0.000	0.000
C20	0.000	0.000	0.000	0.000	0.111	0.000	0.111

Table 12. Mean Below Utilities

	A1	A2	A3	A4	A5	A6	A7
C1	0.000	0.000	0.000	0.000	0.000	0.000	0.000
C2	0.000	0.000	0.000	0.000	0.000	0.000	0.000
C3	0.000	0.000	0.000	0.000	0.000	0.000	0.000
C4	0.000	0.000	0.000	0.000	0.000	0.000	0.000
C5	0.000	0.000	0.000	0.000	0.000	0.000	0.000
C6	0.000	0.000	0.000	0.000	0.000	0.000	0.000
C7	0.036	0.000	0.000	0.000	0.092	0.000	0.000
C8	0.000	0.000	0.000	0.000	0.071	0.000	0.000
C9	0.000	0.000	0.000	0.000	0.000	0.000	0.000
C10	0.000	0.000	0.000	0.000	0.000	0.000	0.000
C11	0.000	0.000	0.000	0.000	0.000	0.000	0.000
C12	0.000	0.058	0.000	0.052	0.058	0.000	0.000
C13	0.000	0.000	0.000	0.000	0.000	0.000	0.000
C14	0.000	0.000	0.000	0.000	0.000	0.000	0.000
C15	0.000	0.000	0.000	0.000	0.000	0.000	0.000
C16	0.000	0.000	0.000	0.030	0.000	0.030	0.000
C17	0.018	0.000	0.000	0.000	0.000	0.054	0.000
C18	0.000	0.000	0.000	0.000	0.000	0.000	0.000
C19	0.000	0.000	0.000	0.000	0.000	0.000	0.000
C20	0.111	0.000	0.111	0.000	0.000	0.000	0.000

Table 13. Mean above losses

	A1	A2	A3	A4	A5	A6	A7
C1	0.000	0.000	0.000	0.000	0.000	0.000	0.000
C2	0.000	0.000	0.000	0.000	0.000	0.000	0.000
C3	0.000	0.000	0.000	0.000	0.000	0.000	0.210526
C4	0.000	0.000	0.000	0.000	0.000	0.000	0.000

	A1	A2	A3	A4	A5	A6	A7
C5	0.000	0.000	0.047	0.000	0.000	0.000	0.000
C6	0.000	0.000	0.000	0.000	0.000	0.000	0.000
C7	0.000	0.06	0.000	0.000	0.000	0.225	0.000
C8	0.000	0.100	0.000	0.000	0.000	0.000	0.000
C9	0.000	0.000	0.000	0.000	0.000	0.000	0.000
C10	0.000	0.000	0.000	0.000	0.000	0.000	0.000
C11	0.000	0.000	0.000	0.000	0.000	0.000	0.000
C12	0.000	0.000	0.000	0.000	0.000	0.000	0.000
C13	0.000	0.000	0.000	0.000	0.000	0.000	0.000
C14	0.000	0.000	0.000	0.000	0.000	0.000	0.000
C15	0.000	0.000	0.000	0.000	0.000	0.000	0.000
C16	0.000	0.000	0.045	0.000	0.000	0.000	0.000
C17	0.000	0.087	0.000	0.000	0.000	0.000	0.000
C18	0.000	0.000	0.200	0.000	0.000	0.000	0.000
C19	0.000	0.000	0.000	0.000	0.000	0.000	0.000
C20	0.000	0.000	0.000	0.000	0.000	0.250	0.000

Table 14. Mean below losses

	A1	A2	A3	A4	A5	A6	A7
C1	0.000	0.000	0.000	0.000	0.000	0.000	0.000
C2	0.000	0.000	0.000	0.000	0.000	0.000	0.000
C3	0.052	0.000	0.052	0.052	0.0526	0.000	0.000
C4	0.000	0.000	0.000	0.000	0.000	0.000	0.000
C5	0.0158	0.000	0.000	0.000	0.000	0.015	0.015
C6	0.000	0.000	0.000	0.000	0.000	0.000	0.000
C7	0.000	0.000	0.184	0.102	0.000	0.000	0.000
C8	0.000	0.000	0.000	0.1	0.000	0.000	0.000
C9	0.000	0.000	0.000	0.000	0.000	0.000	0.000
C10	0.000	0.000	0.000	0.000	0.000	0.000	0.000
C11	0.000	0.000	0.000	0.000	0.000	0.000	0.000
C12	3.4364E-17	0.000	3.4364E-17	0.000	0.000	0.000	3.4364E-17
C13	0.000	0.000	0.000	0.000	0.000	0.000	0.000
C14	0.000	0.000	0.000	0.000	0.000	0.000	0.000
C15	0.000	0.000	0.000	0.000	0.000	0.000	0.000
C16	0.022	0.000	0.000	0.000	0.000	0.000	0.022
C17	0.000	0.000	0.000	0.0875	0.000	0.000	0.000
C18	0.066	0.000	0.000	0.066	0.000	0.000	0.066
C19	0.000	0.000	0.000	0	0.000	0.000	0.000
C20	0.000	0.125	0.000	0.125	0.000	0.000	0.000

Step 5. *Calculating the weights of the criteria considering the interactions using R.Graph*

Using the R.Graph method the relative weight of each attribute is determined by analyzing its impact on the other criteria within the system using Eqs. (25)-(27). The result is in Table 15.

Table 115. Weights of Criteria Considering the Interactions

Criteria	Weight	Criteria	Weight	Criteria	Weight	Criteria	Weight
C1	0.062	C6	0.056	C11	0.034	C16	0.087
C2	0.072	C7	0.051	C12	0.030	C17	0.077
C3	0.069	C8	0.047	C13	0.025	C18	0.069
C4	0.065	C9	0.043	C14	0.021	C19	0.052
C5	0.061	C10	0.039	C15	0.017	C20	0.014

Step 6. *Calculating the Total Utility and Total Loss of Each Alternative*

Now, the total utility and total loss for each alternative are calculated. First, by combining the summarized weighted values obtained using Eqs. (28) and (29), the total utility is calculated using Eq. (30), while the total loss is determined using Eq .(31). These calculations provide a final metric that reflects the balance between the positive and negative attributes of each alternative, facilitating a clear comparison among them. The results of these calculations, which are essential for the final decision-making process, are presented in Table 16.

Table 16. Total Utilities and Total Losses

Alternatives	Total Utilities	Total Losses
A1	0.025	0.054
A2	0.092	0.052
A3	0.015	0.099
A4	0.035	0.034
A5	0.078	0.024
A6	0.094	0.047
A7	0.054	0.113

Step 7. *Calculating the Appraisal Score (AS) of Each Option*

In this step, the appraisal score is calculated for each alternative using the total utility and total loss values obtained from the previous step. The appraisal score is calculated using Eq.(32), which combines the total utility and total loss to derive a comprehensive evaluation metric. This calculation is performed in two sections: one without considering interaction effects and another that takes interactions into account. The results from both approaches are essential for understanding the impact of interactions on the final scores and are presented in Table 20.

Table 20. Appraisal Score for each Alternative

Appraisal Score						
Not considering interaction						
A1	**A2**	**A3**	**A4**	**A5**	**A6**	**A7**
1.280	1.660	0.209	1.049	1.468	1.355	0.576
Considering interaction						

1.476	1.669	0.246	1.038	1.495	1.530	0.533

Now, the alternatives are ranked based on the appraisal scores calculated in the previous step. The final ranking of the alternatives, which reflects their performance across all evaluated criteria, is presented in Table 21.

Table 21. Rank of Alternatives

Alternative	Rank (not considering interaction)	Rank (considering interaction)
BERT (A_1)	4	4
GPT (A_2)	1	1
Transformer-XL (A_3)	7	7
XLNet (A_4)	5	5
RoBERTa (A_5)	2	3
T5 (A_6)	3	2
DistilBERT (A_7)	6	6

5.2. Validation of the results

Multi-attribute decision-making (MADM) techniques strive to deliver dependable and consistent results. However, the rankings they produce may vary due to changes like adjustments in criterion weights, the addition or removal of alternatives, subjective evaluations, and the precise selection of criteria. In this section, the results from the case study are verified using various methods. In Section 5.2.1, the ranking outcomes from the case study are evaluated against those of prevalent MADM methods found in scholarly articles, examining their correlations. Section 5.2.2 explores the stability of these ranking results by assessing how they respond to changes in the input weights.

5.2.1. Ranking results of other methods

In this section, the outcomes of the EDAS method are juxtaposed with those from various ranking methods to determine the similarity or disparity in the final rankings. This decision matrix is solved using these ranking methods, i.e., EDAS [37], VIKOR, MABAC [38], TODIM [39], WASPAS [40], MACBETH [41], EVAMIX [42], TOPSIS [43]. The results are presented in Table 22, where the differences in rankings are highlighted in blue. In addition, Spearman's correlation coefficient results The Spearman correlation matrix illustrated above offers a detailed examination of the rank correlations between various MADM methods. The matrix assesses the monotonic relationships among the rankings generated by these methods, providing key insights into their consistency and agreement. between the ranking of the proposed method and the other methods are depicted in Fig. 7 and Table 22.

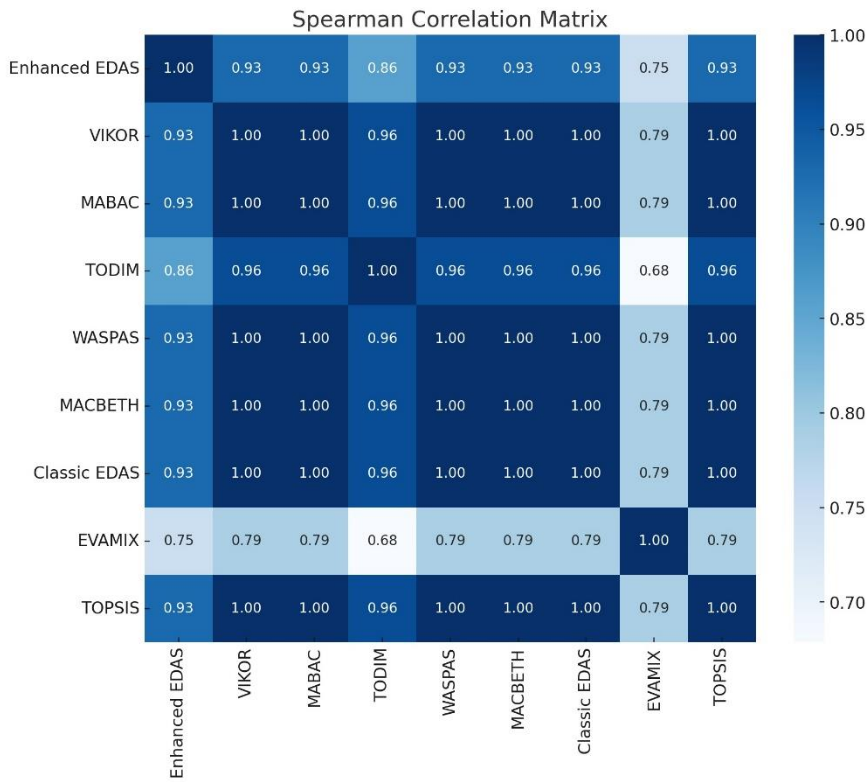


Figure 6. Spearman Correlation

To measure the differences between ranking results, we further employed three statistical methods: Kendall's Tau Correlation Matrix [44], Distance Matrix [45], and Agreement Measure [46]. Kendall's Tau Correlation Matrix (Fig. 8) assesses the ordinal relationships among various MCDM methods, illustrating the extent to which these methods rank the same items similarly. The Distance Matrix (Fig. 9) calculates the Euclidean distance between the rankings, offering insights into the differences among the methods. Finally, Cohen's Kappa Agreement Measure (Fig. 10) evaluates the level of agreement between method pairs while accounting for the likelihood of chance agreement.

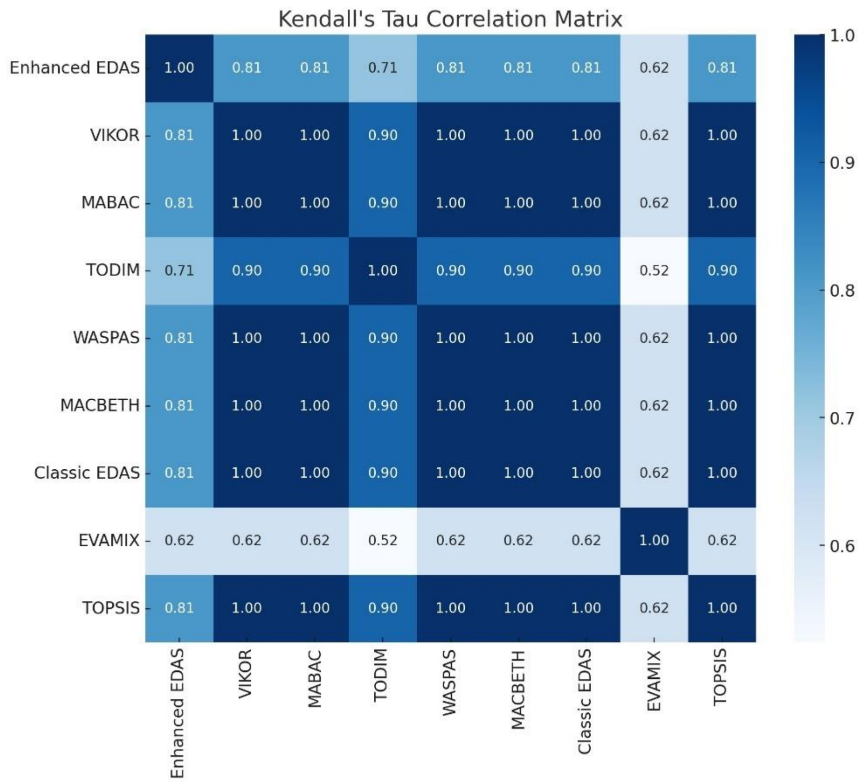


Figure 7. Kendall's Tau Correlation Matrix

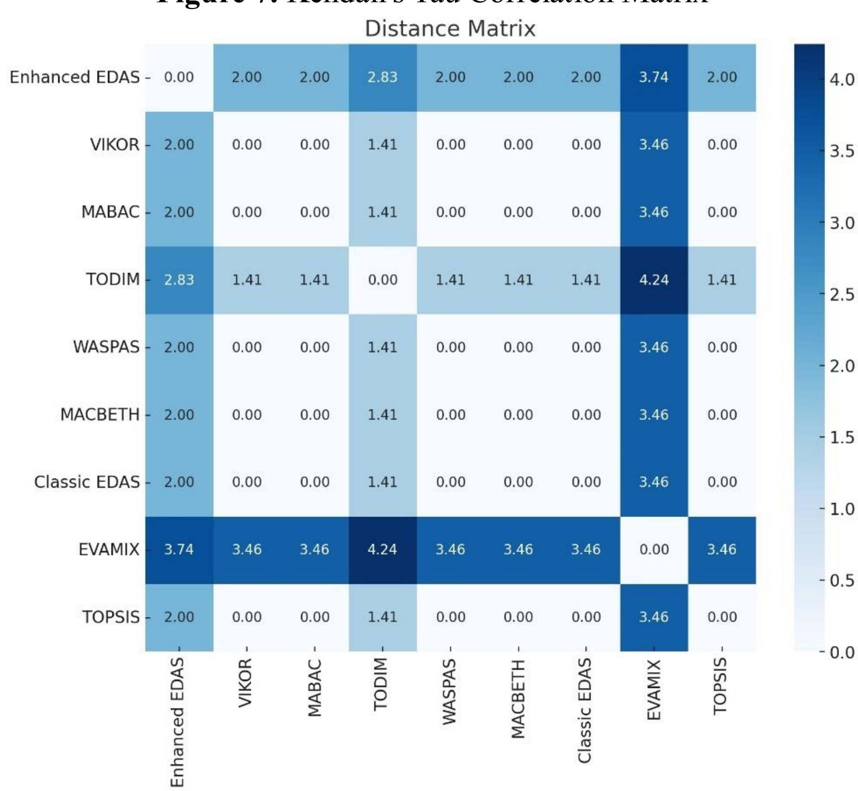


Figure 8. Distance Matrix

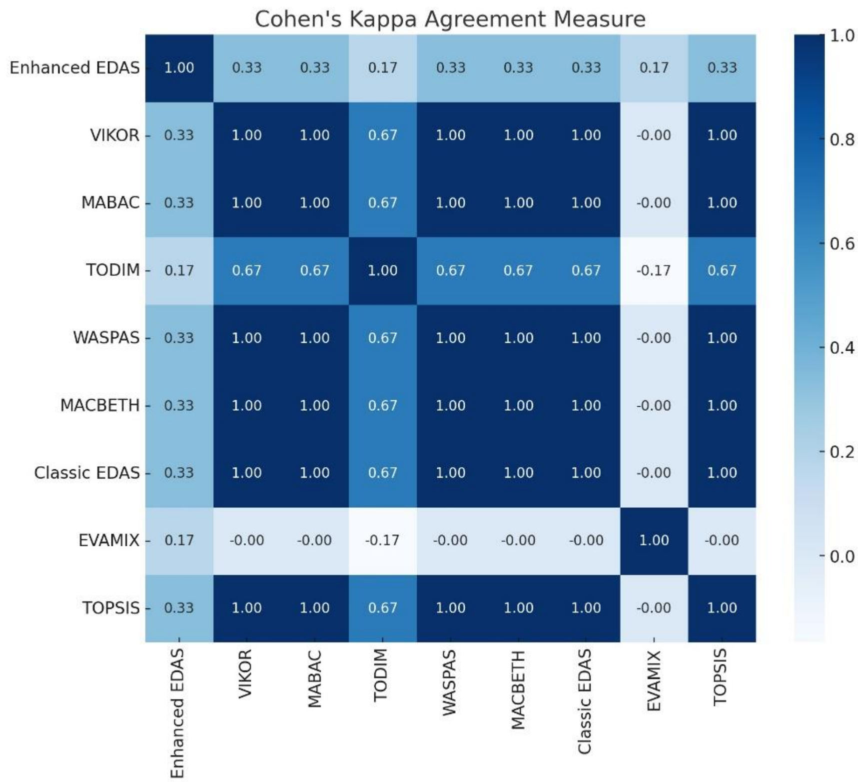


Figure 9. Cohen's Kappa Agreement Measure

Table 17. Ranking results of other MADM approaches.

	Raking Comparison																	
	Proposed method		VIKOR S		TOPSIS		MACBETH		WASPAS		TODIM		Classic EDAS		EVAMIX		MABAC	
	Rank	Utility	Rank	Utility	Rank	Utility	Rank	Utility	Rank	Utility	Rank	Utility	Rank	Utility	Rank	Utility	Rank	Utility
A1	4	1.476	4	0.639	5	0.445	5	36.0	5	0.805	5	0.451	5	0.340	6	4.10	5	0.360
A2	1	1.669	1	0.150	1	0.633	1	84.9	1	0.921	2	0.903	1	0.892	1	10.0	1	0.849
A3	7	0.246	7	0.850	7	0.333	7	14.9	7	0.753	7	0.000	7	0.086	5	4.32	7	0.149
A4	5	1.038	5	0.440	4	0.533	4	55.9	4	0.843	4	0.551	4	0.525	3	6.88	4	0.559
A5	3	1.495	3	0.216	2	0.622	2	78.3	2	0.904	1	1.000	2	0.824	4	6.64	2	0.783
A6	2	1.530	2	0.278	3	0.597	3	72.1	3	0.899	3	0.776	3	0.785	2	7.01	3	0.721
A7	6	0.533	6	0.782	6	0.392	6	21.7	6	0.774	6	0.012	6	0.162	7	3.00	6	0.217

5.2.2. *sensitivity analysis*

The purpose of performing a sensitivity analysis within a specific MADM algorithm is to explore how alterations in predefined conditions affect the derived rankings. This analysis is crucial for evaluating the robustness of the MADM method's results. Variations in criteria weights are particularly influential in modifying these conditions and impacting the outcomes of MADM methods. In this section, the resilience of the results to intentional adjustments in the input weight matrix is examined. Given that subjective weights are a primary focus for decision-makers in this case study, an error percentage is applied to the obtained weight values to assess its impact on the overall performance of the options. For instance, if we aim to determine how sensitive the outcomes are to variations in the weights w_j we can consider a certain percentage of change and error in w_j as er. The adjusted weight, denoted as w_j^m, can then be calculated using the relation below:

$$w_j^m = \left(1 - \frac{er}{100}\right) w_j \tag{33}$$

And other modified attributes weight due to the change in w^j is calculated as:

$$w_i = \frac{\left(1-\left(1-\frac{er}{100}\right)w_j\right)w_i}{1-w_j} \qquad \forall\, i = 1, \dots m,\ j = 1, \dots, n \tag{34}$$

For analyzing the sensitivity, we consider 13 different values for er, i.e.,

$\text{Er} \in \{-100\%, -77\%, -55\%, -33\%, -11\%, 11\%, 33\%, 55\%, 77\%, 100\%\}$

The overall performances of all alternatives are computed for each percentage error value and corresponding modified weights, and a scatter plot displaying these data points is presented in Fig. 11.

The radar charts presented in the Fig. 11. provide a comprehensive visual analysis of the weight sensitivity across various attributes under different weight change scenarios. Each chart corresponds to a specific attribute, with the radar plots illustrating how the relative importance (weights) assigned to that attribute varies across ten distinct scenarios, ranging from a -100% to a +100% change. This analysis is critical for understanding the robustness of the decision-making process to variations in attribute weights. Notably, most attributes exhibit a stable pattern across the different scenarios, indicating that the overall decision is not overly sensitive to weight fluctuations. However, some attributes, such as Attributes 7, 8 and 9, show more pronounced variations across scenarios, suggesting that these attributes may have a more significant impact on the final decision outcome. This weight sensitivity analysis thus highlights which attributes are most influential and how variations in their assigned importance could potentially alter the ranking of alternatives in the decision-making process. Such insights are crucial for decision-makers to ensure that their choices are resilient to changes in the weighting of criteria, thereby enhancing the reliability and validity of the decision model.

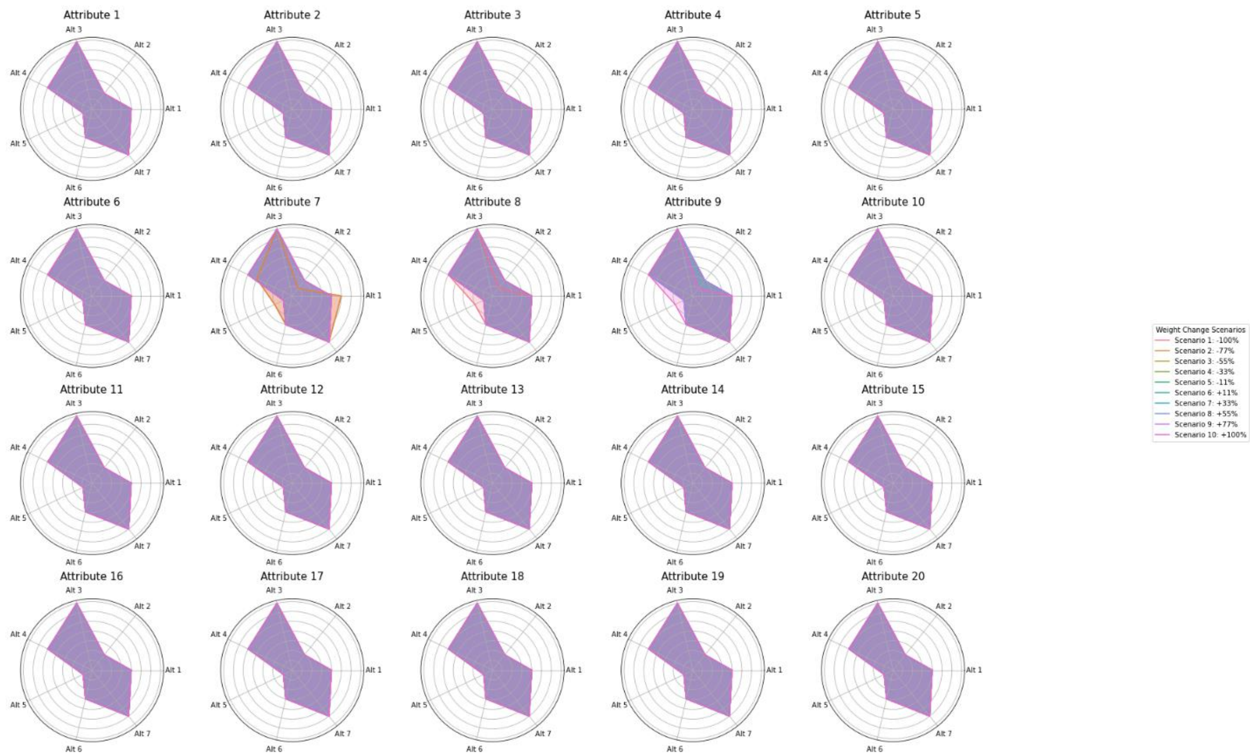


Figure 10. Weight sensitivity analysis

5.3. *Discussion and managerial insights*

This study's findings underscore the critical role of advanced AI techniques, particularly GAI and NLP-based models, in enhancing supply chain risk management. By strategically selecting these technologies, organizations can significantly improve their capability to predict, mitigate, and respond to disruptions throughout the supply chain. The development of the R.Graph-Enhanced EDAS method as a new MCDM tool offers a structured approach for evaluating various AI models, facilitating more informed decisions aligned with specific organizational goals. The case study results demonstrate the effectiveness of the R.Graph-Enhanced EDAS method in systematically assessing different AI models against multiple criteria. This method allows organizations to consider trade-offs and interactions between different criteria, ensuring that the selected models are not only efficient but also scalable and adaptable to diverse risk scenarios. Consequently, this approach enhances the robustness and resilience of supply chain operations by enabling proactive and adaptive risk management strategies.

The results reveal that most correlations are exceptionally high, with many values exceeding 0.90, indicating strong agreement in the ranking results produced by these methods. For instance, the Enhanced EDAS method shows a strong correlation with Classic EDAS (0.81), signifying identical or nearly identical rankings. Similarly, VIKOR, MABAC, and WASPAS exhibit high correlations with each other (0.93 - 1.00), reflecting a consistent ranking order among alternatives. Moderate correlation values (0.75 to 0.86) are also observed, such as TODIM's correlation with Enhanced EDAS (0.70) and VIKOR (0.9). These correlations suggest general alignment in rankings, with occasional differences likely due to distinct principles or weighting strategies. The matrix highlights lower correlations, particularly with EVAMIX, which shows moderate correlations with MABAC and WASPAS (0.62). This suggests EVAMIX may generate different ranking orders due to its unique evaluation approach. The variability in correlations underscores the potential diversity in decision-making outcomes when applying different MCDM methods. The generally high correlations indicate robust consensus in ranking outcomes, enhancing decision-making reliability. However, moderate correlations with methods like EVAMIX and TODIM highlight the importance of selecting a method based on the specific characteristics of the decision problem.

Our proposed R.Graph-Enhanced EDAS method introduces a critical advancement by considering interactions between criteria and calculating utility and loss values relative to the mean of all alternatives, similar to the classic EDAS method. However, it adds a key distinction by evaluating the performance of each alternative not only against the best and worst alternatives but also relative to the other alternatives selected as utilities or losses. This additional layer of comparison sets it apart from simpler EDAS methods.

In the R.Graph-Enhanced EDAS, alternatives are first assessed in comparison to one another, and only after this are they separately compared to the best and worst-performing alternatives. This nuanced approach explains why the ranking results differ from other methods. For example, the rank of Alternative A1 initially positioned at 5, and A4 at 4, is reversed in our method, with A1 now ranked 4 and A4 ranked 5. Similarly, the ranks of Alternative 5 and Alternative 6 switch places from 2 and 3, to 3 and 2, respectively. This illustrates how Alternative A4 outperforms A4 in absolute value across certain attributes, but when comparing performance based on best values, Alternative A1 exhibits superior performance in specific criteria.

Furthermore, the inclusion of interactions between criteria leads to noticeable shifts in the rankings of Alternatives 5 and 6, demonstrating the unique influence of the R.Graph method. It is also worth noting that while there are some differences when considering interactions versus not considering them, the final rankings remain relatively stable due to the high number of attributes. The large number of attributes reduces sensitivity to changes in weights, causing shifts in the appraisal scores without significantly altering the overall ranking. This robustness underscores the method's strength in handling complex, multi-criteria decision problems.

In this study, GPT has been selected as the best generative AI model for managing supply chain risks in the food supply chain. While this might seem predictable at first glance due to the advancements and widespread applications of GPT compared to models such as BERT (A1), Transformer-XL (A3), XLNet (A4), RoBERTa (A5), T5 (A6), and DistilBERT (A7), it is essential to conduct a thorough analysis considering various economic and human-centric criteria to validate this choice.

Among the key human-centric criteria such as **Data Privacy Measures Implemented (C6)**, **Model Training Time and Complexity (C7)**, and **Scalability with Data Volume Increases (C13)** are critical to ensuring that the model is not only efficient but also adaptable to the specific needs of the supply chain environment. GPT’s superior performance across these criteria makes it a standout choice. Its ability to handle vast amounts of data and produce accurate predictions regarding demand volatility and supplier disruptions is critical for maintaining resilience in the food supply chain. Moreover, GPT's capability to process complex data patterns enables it to identify production bottlenecks and detect inventory imbalances more effectively than other models. Its scalable architecture also ensures that organizations can seamlessly expand their operations without being hindered by data volume constraints.

Organizations can apply GPT to enhance decision-making processes by leveraging its accuracy in predicting risks and disruptions, improving the speed of decision-making (C18), and increasing communication efficiency (C19) across the supply chain. Furthermore, GPT’s adaptability allows it to tailor solutions to industry-specific requirements (C12), ensuring that it meets the unique challenges faced by the food supply chain. By implementing GPT, organizations can proactively manage risks, reduce costs (C17), and optimize their supply chain operations, leading to more resilient and efficient systems.

From a managerial perspective, the implementation of AI-driven risk management strategies offers several key advantages:

- **Enhanced Decision-Making**: The proposed method equips managers with a clear and structured framework to assess and compare various AI models, facilitating more informed decision-making. This approach helps managers understand the strengths and weaknesses of each model in relation to specific supply chain risks, ensuring that the most effective solutions are chosen.
- **Improved Risk Mitigation**: GPT models, with their ability to process vast amounts of data in real-time, allow for early detection of potential disruptions. This capability enables managers to implement preemptive measures, reducing the overall impact of risks on supply chain operations and ensuring smoother processes.
- **Scalability and Adaptability**: The study demonstrates that AI models, when carefully selected and integrated, can be effectively scaled across various supply chain functions

and adapted to evolving market conditions. This adaptability is critical in maintaining operational efficiency and continuity, particularly when facing unexpected challenges.

- **Strategic Investment in Technology**: The findings highlight the importance of investing in advanced AI technologies, particularly GPT. Such strategic investments can enhance supply chain resilience, significantly reduce the costs associated with disruptions, and provide long-term benefits by improving the robustness of supply chain operations.

By embracing these AI-driven strategies, organizations can not only mitigate risks more effectively but also optimize their overall supply chain performance in dynamic and unpredictable environments

6. Conclusion

This research has addressed the significant challenge of selecting the most effective GAI transformer model for supply chain risk management by proposing R,Graph-Enhanced EDAS method. By refining the logical structure of this method and incorporating interactions and interdependencies between criteria, we developed a more robust and comprehensive multi-criteria decision-making framework. Applying this improved model to the food supply chain context demonstrated that the Generative Pre-trained Transformer is particularly well-suited for managing complex and dynamic supply chain risks, showcasing superior performance across multiple risk factors. The contributions of this study extend beyond the immediate context of food supply chains, offering a versatile decision-making tool applicable to various industries facing similar challenges. By integrating human-centric criteria, the framework ensures that AI models are selected based on ethical standards and practical needs, supporting more transparent, effective, and responsible supply chain management.

Future studies could explore the application of proposed framework in a broader range of industries, testing its adaptability and effectiveness across diverse supply chain environments such as healthcare, manufacturing, and retail [11]. Additionally, incorporating real-time data analytics into the decision-making process could further enhance the framework's agility and responsiveness, allowing it to adapt to rapidly changing conditions in global supply chains [47]. Integrating advanced AI techniques, such as machine learning or deep learning could also improve its predictive accuracy and decision support capabilities [48]. Moreover, investigating the ethical implications of AI in supply chain management, particularly in terms of fairness, transparency, and accountability, could lead to the development of comprehensive guidelines for the responsible use of AI across different sectors [49]. These future studies will be crucial in ensuring that AI technologies not only optimize supply chain operations but also align with broader societal values and contribute to sustainable and equitable global supply chains [50].

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the authors used OpenAI's tool Chat GPT in order to edit and write some parts of the paper. After using this service, the authors reviewed and edited the content as needed and took full responsibility for the content of the publication.

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Appendix A (Questionnaire)

Instructions: For each question, please provide the percentage change or numerical value based on the scenario described. The questionnaire aims to assess the impacts and relationships between criteria.

For all questions related to Criteria, assume a 100% percentage change in the value of the criteria.

1. For Criteria 1 (Accuracy of Demand Volatility Predictions); what is the percentage change in the criteria "Cost Reduction in Risk Management" (C17), and "Improvement in Decision-making Speed" (C18) if Criteria 1 changes?
    - Cost Reduction in Risk Management (C17):

- Improvement in Decision-making Speed (C18):

2. For Criteria 2 (Timeliness of Supplier Disruption Alerts); what is the percentage change in the criteria “Percentage Reduction in Disruptions” (C16), and “Efficiency Gains in Communication” (C19) if Criteria 2 changes?
   - Percentage Reduction in Disruptions (C16):
   - Efficiency Gains in Communication (C19):
3. For Criteria 3 (Precision in Transportation Delay Forecasts); what is the percentage change in the criteria “Scalability with Data Volume Increases” (C13) if Criteria 3 changes?
   - Scalability with Data Volume Increases (C13):
4. For Criteria 4 (Detection Rate of Inventory Imbalances); what is the percentage change in the criteria “Accuracy of Demand Volatility Predictions” (C1) if Criteria 4 changes?
   - Accuracy of Demand Volatility Predictions (C1):
5. For Criteria 5 (Identification Rate of Production Bottlenecks); what is the percentage change in the criteria “Timeliness of Supplier Disruption Alerts” (C2), and “Improvement in Decision-making Speed” (C18) if Criteria 5 changes?
   - Timeliness of Supplier Disruption Alerts (C2):
   - Improvement in Decision-making Speed (C18):
6. For Criteria 6 (Data Privacy Measures Implemented); what is the percentage change in the criteria “Adherence to Regulatory Standards” (C10) if Criteria 6 changes?
   - Adherence to Regulatory Standards (C10):
7. For Criteria 7 (Model Training Time and Complexity); what is the percentage change in the criteria “Initial Implementation Costs” (C8), and “Compatibility with Existing IT Infrastructure” (C14) if Criteria 7 changes?
   - Initial Implementation Costs (C8):
   - Compatibility with Existing IT Infrastructure (C14):
8. For Criteria 8 (Initial Implementation Costs); what is the percentage change in the criteria “Scalability with Data Volume Increases” (C13), and “Ease of Model Version Control” (C15) if Criteria 8 changes?
   - Scalability with Data Volume Increases (C13):
   - Ease of Model Version Control (C15):
9. For Criteria 9 (Computational Resources Utilization); what is the percentage change in the criteria “Precision in Transportation Delay Forecasts” (C3) if Criteria 9 changes?
   - Precision in Transportation Delay Forecasts (C3):
10. For Criteria 10 (Adherence to Regulatory Standards); what is the percentage change in the criteria and “Compatibility with Existing IT Infrastructure” (C14) if Criteria 10 changes?
    - Compatibility with Existing IT Infrastructure (C14):

11. For Criteria 11 (Frequency of Real-time Updates); what is the percentage change in the criteria “Improvement in Decision-making Speed” (C18) if Criteria 11 changes?
    - Improvement in Decision-making Speed (C18):
12. For Criteria 12 (Tailored Solutions for Industry Specifics); what is the percentage change in the criteria “Scalability with Data Volume Increases” (C13), and “Compatibility with Existing IT Infrastructure” (C14) if Criteria 12 changes?
    - Scalability with Data Volume Increases (C13):
    - Compatibility with Existing IT Infrastructure (C14):
13. For Criteria 13 (Scalability with Data Volume Increases); what is the percentage change in the criteria “Computational Resources Utilization” (C9), and “Compatibility with Existing IT Infrastructure” (C14) if Criteria 13 changes?
    - Computational Resources Utilization (C9):
    - Compatibility with Existing IT Infrastructure (C14):
14. For Criteria 14 (Compatibility with Existing IT Infrastructure); what is the percentage change in the criteria “Ease of Model Version Control” (C15), and “Energy-Efficient Model Design” (C20) if Criteria 14 changes?
    - Ease of Model Version Control (C15):
    - Energy-Efficient Model Design (C20):
15. For Criteria 15 (Ease of Model Version Control); what is the percentage change in the criteria “Data Privacy Measures Implemented” (C6) if Criteria 15 changes?
    - Data Privacy Measures Implemented (C6):
16. For Criteria 16 (Percentage Reduction in Disruptions); what is the percentage change in the criteria “Accuracy of Demand Volatility Predictions” (C1), and “Cost Reduction in Risk Management” (C17) if Criteria 16 changes?
    - Accuracy of Demand Volatility Predictions (C1):
    - Cost Reduction in Risk Management (C17):
17. For Criteria 17 (Cost Reduction in Risk Management); what is the percentage change in the criteria “Detection Rate of Inventory Imbalances” (C4) if Criteria 17 changes?
    - Detection Rate of Inventory Imbalances (C4):
18. For Criteria 18 (Improvement in Decision-making Speed); what is the percentage change in the criteria “Timeliness of Supplier Disruption Alerts” (C2) if Criteria 18 changes?
    - Timeliness of Supplier Disruption Alerts (C2):
19. For Criteria 19 (Efficiency Gains in Communication); what is the percentage change in the criteria “Frequency of Real-time Updates” (C11) if Criteria 19 changes?
    - Frequency of Real-time Updates (C11):

20. For Criteria 20 (Energy-Efficient Model Design); what is the percentage change in the criteria "Computational Resources Utilization" (C9), and "Ease of Model Version Control" (C15) if Criteria 20 changes?
    - Computational Resources Utilization (C9):
    - Ease of Model Version Control (C15):

Appendix B

1. Accuracy of Demand Volatility Predictions (C1):
    a. Cost Reduction in Risk Management (C17): Positive correlation (e.g., +60%): Improved accuracy in demand volatility predictions can contribute to cost reduction in risk management.
    b. Improvement in Decision-making Speed (C18): Positive correlation (e.g., +50%): Accurate demand volatility predictions can help improve decision-making speed.
2. Timeliness of Supplier Disruption Alerts (C2):
    a. Percentage Reduction in Disruptions (C16): Positive correlation (e.g., +40%): Timely supplier disruption alerts may contribute to a higher percentage reduction in disruptions.
    b. Efficiency Gains in Communication (C19): Positive correlation (e.g., +40%): Timeliness of supplier disruption alerts can lead to efficiency gains in communication.
3. Precision in Transportation Delay Forecasts (C3):
    a. Scalability with Data Volume Increases (C13): Positive correlation (e.g., +30%): Precise transportation delay forecasts can support scalability with increasing data volumes.
4. Detection Rate of Inventory Imbalances (C4):
    a. Accuracy of Demand Volatility Predictions (C1): Positive correlation (e.g., +70%): A higher detection rate of inventory imbalances can contribute to improved accuracy in demand volatility predictions.
5. Identification Rate of Production Bottlenecks (C5):
    a. Timeliness of Supplier Disruption Alerts (C2): Positive correlation (e.g., +60%): Higher identification rate of production bottlenecks can facilitate timely supplier disruption alerts.
    b. Improvement in Decision-making Speed (C18): Positive correlation (e.g., +40%): A higher identification rate of production bottlenecks can lead to improved decision-making speed.
6. Data Privacy Measures Implemented (C6):
    a. Adherence to Regulatory Standards (C10): Positive correlation (e.g., +50%): Implementation of data privacy measures is likely to be influenced by the need to adhere to regulatory standards.
7. Model Training Time and Complexity (C7):

    a. Initial Implementation Costs (C8): Positive correlation (e.g., +60%): Longer training times or complex models may increase initial implementation costs.
    b. Compatibility with Existing IT Infrastructure (C14): Positive correlation (e.g., +40%): Model training time and complexity can impact the compatibility with existing IT infrastructure.
8. Initial Implementation Costs (C8):
    a. Scalability with Data Volume Increases (C13): Negative correlation (e.g., -30%): Higher initial implementation costs might affect the scalability with increasing data volumes.
    b. Ease of Model Version Control (C15): Negative correlation (e.g., -50%): Higher initial implementation costs may make it more challenging to establish easy model version control.
9. Computational Resources Utilization (C9):
    a. Precision in Transportation Delay Forecasts (C3): Positive correlation (e.g., +50%): Efficient utilization of computational resources can improve the precision in transportation delay forecasts.
10. Adherence to Regulatory Standards (C10):
    a. Compatibility with Existing IT Infrastructure (C14): Positive correlation (e.g., +40%): Adherence to regulatory standards can affect the compatibility with existing IT infrastructure.
11. Frequency of Real-time Updates (C11):
    a. Improvement in Decision-making Speed (C18): Positive correlation (e.g., +40%): More frequent real-time updates can contribute to improved decision-making speed.
12. Tailored Solutions for Industry Specifics (C12):
    a. Scalability with Data Volume Increases (C13): Positive correlation (e.g., +50%): Tailored solutions can be designed to accommodate industry-specific needs and ensure scalability with increasing data volumes.
    b. Compatibility with Existing IT Infrastructure (C14): Positive correlation (e.g., +40%): Tailored solutions may impact the compatibility with existing IT infrastructure.
13. Scalability with Data Volume Increases (C13):
    a. Computational Resources Utilization (C9): Positive correlation (e.g., +50%): Scalability with data volume increases requires efficient utilization of computational resources.
    b. Compatibility with Existing IT Infrastructure (C14): Positive correlation (e.g., +40%): Scalability with data volume increases can be influenced by the compatibility with existing IT infrastructure.

14. Compatibility with Existing IT Infrastructure (C14):
    a. Ease of Model Version Control (C15): Positive correlation (e.g., +50%): Compatibility with existing IT infrastructure can impact the ease of model version control.
    b. Energy-Efficient Model Design (C20): Positive correlation (e.g., +40%): Compatibility with existing IT infrastructure may influence the development of energy-efficient model designs.
15. Ease of Model Version Control (C15):
    a. Data Privacy Measures Implemented (C6): Positive correlation (e.g., +40%): Easy model version control can support the implementation of data privacy measures.
16. Percentage Reduction in Disruptions (C16):
    a. Accuracy of Demand Volatility Predictions (C1): Positive correlation (e.g., +60%): A higher percentage reduction in disruptions can be associated with improved accuracy in demand volatility predictions.
    b. Cost Reduction in Risk Management (C17): Positive correlation (e.g., +50%): A greater reduction in disruptions can contribute to cost reduction in risk management.
17. Cost Reduction in Risk Management (C17):
    a. Detection Rate of Inventory Imbalances (C4): Positive correlation (e.g., +50%): Higher cost reduction in risk management may lead to a higher detection rate of inventory imbalances.
18. Improvement in Decision-making Speed (C18):
    a. Timeliness of Supplier Disruption Alerts (C2): Positive correlation (e.g., +40%): Faster decision-making can be facilitated by timely supplier disruption alerts.
19. Efficiency Gains in Communication (C19):
    a. Frequency of Real-time Updates (C11): Positive correlation (e.g., +30%): More efficient communication can promote more frequent real-time updates.
20. Energy-Efficient Model Design (C20):
    a. Computational Resources Utilization (C9): Positive correlation (e.g., +40%): Energy-efficient model designs can optimize the utilization of computational resources.
    b. Ease of Model Version Control (C15): Positive correlation (e.g., +30%): Energy-efficient model designs may facilitate the ease of model version control.