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Assessing Supplier Disruption Risks Using a Modified Pythagorean Fuzzy SWARA–TOPSIS Approach

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ABSTRACT

As the complexity and uncertainty of global supply chains escalate, disruptions have become an increasingly common challenge in supply chain management. Suppliers, who serve as essential connectors for the seamless movement of goods and materials critical to production and distribution, are often at the center of these disruptions, highlighting their significant impact on the overall stability of the supply chain. This study proposes an innovative approach to assessing supplier disruption risks by combining the Pythagorean Fuzzy Step-wise Weight Assessment Ratio Analysis (PF-SWARA) with the Pythagorean Fuzzy Technique for Order Preference by Similarity to Ideal Solution (PF-TOPSIS). By reviewing the literature and consulting with supply chain experts, eight key risk factors were identified. The PF-SWARA method then quantifies the significance of these risks, while a modified PF-TOPSIS technique calculates each supplier's risk score, facilitating the prioritization of suppliers for targeted improvement. The findings of the study indicate that "natural disasters and geopolitical risks," "financial instability," and "delivery delays" emerge as the top three critical disruption risk factors. Suppliers facing higher disruption risks should therefore formulate improvement strategies that target these three areas.

1. Introduction

As global supply chains become more complex and face increasing uncertainties, disruptions have become increasingly common in supply chain management [1, 2]. Such disruptions often arise from various sources, including natural disasters (such as earthquakes, hurricanes, and floods) [3], human-induced hazards (such as fires, labor strikes, and acts of terrorism) [4], and significant regulatory changes (such as new environmental regulations) [5]. These events can lead to changes in the structure of supply chains and trigger a cascade effect, which describes how disruptions spread through supply chains and affect their design and operational strategies [6]. To mitigate the effects of such disruptions on the entities within the supply chain, managing the cascade effect is crucial.

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The management framework for the cascade effect highlights four key strategies: resilience, redundancy, robustness, and flexibility [7]. Resilience is the capacity of supply chains to effectively prepare for, withstand, and recover from disruptive events. Developing resilient supply chains often involves implementing redundancy strategies that support and are supported by robustness and flexibility [8]. In particular, supply chain robustness is enhanced through proactive measures (such as maintaining safety stocks and establishing alternative sources of supply) to ensure the continuity and efficiency of supply chain operations during the design and planning phases [9].

Suppliers play a crucial role within the supply chain, acting as a pivotal link that ensures the smooth flow of goods and materials necessary for production and distribution processes [10-12]. A significant portion of supply chain disruptions can be attributed to potential issues associated with suppliers. These issues may include delays in delivery, quality problems with supplied goods, the financial instability of suppliers, or even the complete inability of a supplier to fulfill orders due to unforeseen circumstances such as natural disasters or geopolitical tensions [13, 14]. Consequently, the stability and reliability of suppliers are fundamental to maintaining the integrity and efficiency of the entire supply chain. Identifying, assessing, and mitigating risks associated with suppliers are therefore critical steps in supply chain management to prevent disruptions and ensure operational continuity [15, 16].

However, companies should be able to assess the risk of supplier disruptions. This study summarizes eight main potential factors for supplier disruption incidents, including “insufficient production capacity” [17-19], “quality issues” [20-22], “significant price fluctuation” [22-24], “delivery delays” [25-27], “financial instability” [28-30], “changes in local government laws and regulations” [31-33], “technological changes or failures” [15, 18], and “natural disasters and geopolitical risks” [34-36]. Building on these eight risk factors, this paper seeks to explore several critical inquiries: (i) what is the individual hazard level of these disruption risk factors (i.e., the weight of the risk factors)? (ii) how is the risk score of suppliers assessed? (iii) what strategies can be employed to improve the suppliers with higher risk scores? These questions represent typical multiple-criteria decision-making (MCDM) problems [37]. MCDM methods excel in evaluating the performance of alternatives in complex environments. They do not require the basic assumptions of traditional statistics, only a small sample of expert interview data. The objective of MCDM is to formulate the most appropriate strategies for decision-makers and provide effective management information under a complex and interdependent factor environment. Generally, the MCDM process includes determining evaluation criteria, measuring the weights of these criteria, and calculating the performance scores of the evaluated items [38-40].

This paper introduces a novel framework for assessing the risk of supplier disruption. The framework integrates the Pythagorean Fuzzy Step-wise Weight Assessment Ratio Analysis (PF-SWARA) and the Pythagorean Fuzzy TOPSIS (PF-TOPSIS) technique to assess the disruption risk scores of the suppliers. First, eight potential risk factors for supplier disruption are identified through a review of relevant literature and discussions with experts and academics in supply chain management, (as mentioned earlier). Then, the PF-SWARA method is used to determine the importance weights of these risk factors. Finally, a modified PF-TOPSIS technique is used to calculate the risk scores for the suppliers, then based on these scores, the suppliers are prioritized for improvement. This study utilizes the concept of Pythagorean fuzzy theory to extend the uncertainty range beyond that of traditional triangular fuzzy theory, thus more effectively capturing the ambiguity of information during the assessment. Furthermore, the experts’ backgrounds, including their experience, tenure, and educational qualifications, are incorporated to generate weights for their importance. This study enhances the traditional PF-SWARA-TOPSIS approach by refining the ranking index based on the global risk range (the total distance between the highest and lowest risk levels) and incorporates the concept of aspiration level. This modified approach aims to avoid the scenario of selecting the relatively better option from a set of poor choices by setting a benchmark.

This study addresses the gaps identified in past research by providing a comprehensive framework of supplier disruption risk factors. The importance of these disruption risks and the assessment of supplier risks are analyzed using MCDM tools. Furthermore, the proposed approach has been refined to yield more effective and reliable results, incorporating considerations of expert importance and information fuzziness. Focusing on a multinational machine tool manufacturing company in Taiwan, the assessment framework and methodology proposed in this study aim to systematize the process of assessing supplier disruption risks and provide more reliable recommendations for supplier improvement. In summary, the innovations and contributions of this study are summarized as follows:

(i) This study introduces a comprehensive set of eight potential disruption risk factors.
(ii) For the first time, the Pythagorean fuzzy SWARA-TOPSIS approach is applied to assess supplier disruption risks in the machine tool manufacturing industry. Here, this have optimized the previous Pythagorean fuzzy-SWARA-TOPSIS methodology.
(iii) This study incorporates the importance of expert opinions and addresses the uncertainties within the assessment environment to ensure a robust and nuanced assessment.
(iv) This study provides targeted recommendations for improvement to suppliers with a higher risk of disruption, offering practical solutions to mitigate risk and improve supply chain resilience.

The remaining sections are organized as follows. Section 2 reviews the eight supplier disruption risk factors. Section 3 introduces the analysis procedure of the modified PF-SWARA-TOPSIS approach. Section 4 conducts an analysis using real-world data. Section 5 discusses the results, followed by conclusions and directions for future research.

2. Definition of supply disruption risk factors

This section reviews the literature on the eight supply disruption risk factors and explains each in detail.

2.1 Insufficient production capacity

The supply disruption risk associated with insufficient production capacity refers to the potential for disruptions in the supply chain when a supplier is unable to meet demand. This risk arises when a supplier’s manufacturing capabilities are insufficient to produce the required quantity of goods within the required timeframe. Such a shortfall can result from a variety of factors, including limitations in physical resources, technology, manpower, or management constraints. The consequence of this inadequacy is a bottleneck in the supply chain, which leads to delayed deliveries, increased costs, and potentially, the inability to fulfill customer orders. This risk highlights the critical need for suppliers to align their production capacity with the demands of their clients to ensure a smooth and continuous supply chain operation [17-19].

2.2 Quality issues

The supply disruption risk associated with quality issues refers to the potential disruptions in the supply chain caused by the delivery of substandard or defective goods from a supplier. This risk arises when the delivered products fail to meet the predetermined quality standards or specifications agreed upon between the supplier and the buyer. Quality issues can stem from inadequate quality control processes, lack of adherence to quality standards, human error, or the use of inferior materials and components. The consequences of providing low-quality goods are manifold, including the need for returns, replacements, or rework, which can lead to delays, increased costs, and damage to the buyer's brand reputation. Furthermore, persistent quality issues can strain or terminate supplier-buyer relationships. Addressing quality issues is crucial for maintaining the integrity of the supply chain and ensuring the satisfaction and trust of end customers [20-22].

2.3 Significant price fluctuations

The supply disruption risk associated with significant price fluctuations refers to the potential for supply chain instability and operational challenges due to unpredictable and substantial changes in the cost of goods or services provided by suppliers. This risk can be triggered by various factors, including volatile market conditions, changes in raw material costs, economic instability, geopolitical tensions, or changes in supply and demand dynamics. Significant price fluctuations can have a major impact on budgeting, planning, and profitability for buyers, resulting in the need for rapid adjustments in pricing strategies, cost absorption, or even the search for alternative suppliers to maintain cost-effectiveness and competitive pricing for the final products. Managing this risk requires a proactive approach to supply chain management, including diversifying supply sources, establishing long-term contracts with fixed pricing, and developing flexible pricing models with suppliers to mitigate the impact of market volatility on the supply chain [22-24].

2.4 Delivery delays

The supply disruption risk associated with delivery delays refers to the potential for disruptions or inefficiencies in the supply chain caused by the late arrival of goods or materials from suppliers. This risk can arise from a variety of sources, including logistical challenges, production bottlenecks, labor disputes, transportation issues, customs delays, or unexpected surges in demand. Delivery delays can have a cascading effect on the supply chain, impacting production schedules, leading to stock shortages, affecting product launches, and ultimately, disappointing customers. It is important to note that the consequences of delayed deliveries can extend beyond immediate operational concerns, potentially damaging business relationships, brand reputation, and market competitiveness. To mitigate this risk, companies often employ strategies such as maintaining safety stocks, diversifying their supplier base, improving communication channels with suppliers, and implementing sophisticated supply chain management tools for better visibility and forecasting [25-27].

2.5 Financial instability

The supply disruption risk associated with financial instability refers to the potential for supply chain disruptions arising from a supplier's economic difficulties or inability to maintain financial solvency. This risk can manifest itself through various scenarios, such as the supplier's bankruptcy, significant reductions in operational capacity due to cost-cutting measures, or inability to procure necessary materials and resources for production. Financial instability can cause sudden supply halts, forcing companies to scramble for alternative suppliers often at higher costs and under time pressure. The repercussions of a supplier's financial instability are particularly acute for businesses relying on single or limited sources for critical components. To manage this risk, companies may conduct regular financial health assessments of their suppliers, develop contingency plans, and diversify their supplier base to ensure the continuity and resilience of their supply chain [28-30].

2.6 Changes in local government laws and regulations

The supply disruption risk associated with changes in local government laws and regulations refers to the potential for disruptions or complications in the supply chain that arise from modifications to legal frameworks or regulatory policies within a supplier's operating region. Such changes can encompass a wide range of areas, including environmental standards, labor laws, import/export restrictions, tariffs, taxation, and safety regulations. These changes can impact suppliers by requiring adjustments in operational procedures, production methods, or product specifications, which may cause delays, increased costs, or even the cessation of supply. Additionally, new compliance requirements can impose administrative burdens and financial strains on suppliers, further jeopardizing their ability to deliver consistently and efficiently. To mitigate this risk, companies often engage in proactive regulatory monitoring, develop adaptable supply chain strategies that can quickly respond to legal changes, and foster strong communication channels with suppliers to better anticipate and manage potential regulatory impacts [31-33].

2.7 Technological changes or failures

The supply disruption risk associated with technological changes or failures refers to the potential for disruptions in the supply chain due to either the rapid evolution of technology or technological malfunctions within a supplier's operations. Technological changes can render existing products, processes, or machinery obsolete, requiring significant updates or replacements that can disrupt supply timelines. Similarly, technological failures, such as software glitches, hardware breakdowns, or cybersecurity breaches, can halt production or compromise the integrity of supply chain data, leading to delays and potential loss of trust [18].

This risk underscores the importance of staying abreast of technological advancements and maintaining robust information technology (IT) and manufacturing systems that are resilient to failures. Suppliers must invest in regular technology updates, adopt best practices for IT security, and develop contingency plans to address potential technological failures. For the buying company, diversifying the supplier base and fostering innovation within the supply chain can mitigate the impacts of technological changes or failures, ensuring continuous supply and operational flexibility [15].

2.8 Natural disasters and geopolitical risks

The supply disruption risk associated with natural disasters and geopolitical risks refers to potential disruptions in the supply chain caused by unforeseen environmental events or political instability. Natural disasters, such as earthquakes, hurricanes, floods, and wildfires, can severely impact suppliers' operations by damaging facilities, disrupting transportation routes, and causing prolonged outages in production. On the other hand, geopolitical risks, including wars, trade disputes, sanctions, and regulatory changes, can lead to sudden changes in trade patterns, access to materials, and operational legality, affecting suppliers' ability to deliver goods and services [35, 36].

These risks highlight the vulnerability of global supply chains to external shocks that are often beyond the control of individual companies or suppliers. To mitigate these risks, companies can adopt strategies such as diversifying their supplier base across different geographical regions, developing contingency plans for alternative sourcing and logistics, and closely monitoring geopolitical developments. Additionally, investing in supply chain resilience measures, such as flexible inventory strategies and collaborative relationships with suppliers, can enhance the ability to respond effectively to disruptions caused by natural disasters and geopolitical uncertainties [34].

3. The modified PF–SWARA–TOPSIS approach

This section details the implementation and calculation steps of PF-SWARA and PF-TOPSIS. It outlines the methodology for integrating these two advanced decision-making techniques to evaluate and prioritize supplier risks within a specific context. **Figure 1** illustrates the analytical process of the study.

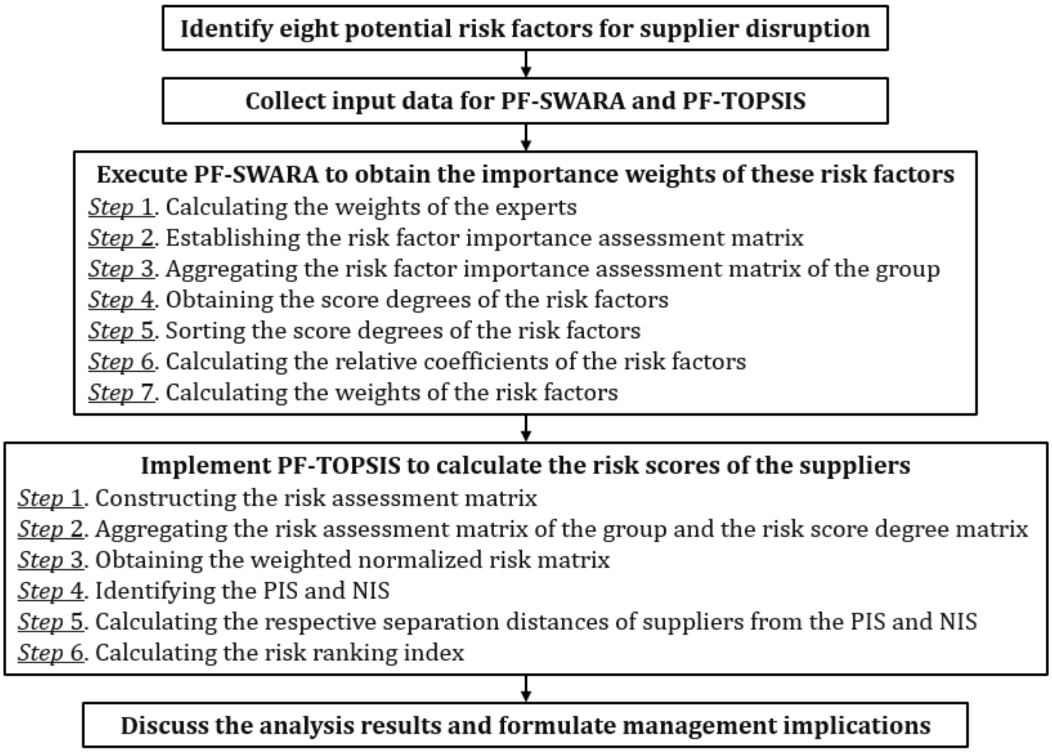

Fig. 1. The analytical process of this study

3.1 PF-SWARA

The SWARA technique, introduced by [41], shares many similarities with the Analytic Hierarchy Process (AHP) method, yet each possesses distinct characteristics. Both methods employ pairwise comparisons to determine the relative importance of elements within a hierarchy, referred to as the Comparative importance of average value in SWARA. This approach is generally appealing to decision-makers participating in evaluations. Unlike AHP, however, SWARA lacks a mechanism for verifying the consistency of comparisons, making it difficult to pinpoint inadequate responses or invalid questionnaires. On the other hand, SWARA requires fewer comparisons than AHP, rendering it more user-friendly for gathering input from general participants [42]. Numerous studies have utilized the SWARA to address weight determination issues across various fields, such as sustainable development solutions of public transportation [43], evaluation of risks impeding sustainable mining [44], road safety assessment [45], climate change risk management [46], etc. Here, considering the integration of uncertainty information and expert judgment, we have incorporated Pythagorean fuzzy sets into SWARA. The implementation steps are as follows.

Step 1. Calculating the weights of the experts

In this study, let k represent the k^{th} expert, where k = 1, 2,…, K. The importance of these experts can be rated using the linguistic variable table presented in Table 1, which can be obtained as

$E=\{E_1, E_2,..., E_k,..., E_K\}$, where $E_k=(\mu_k, \nu_k, \pi_k)$. In Pythagorean fuzzy theory, μ represents the degree of membership, ν represents the degree of non-membership, and π represents the degree of uncertainty. Consequently, all linguistic variables can be transformed into three numerical values corresponding to these degrees. The importance weights of the experts can be calculated using Eq. (1) From this, it is understood that $w_k^{ex.} \geq 0$ and $\sum_{k=1}^{K} w_k^{ex.}=1$.

$$w_k^{ex.}=\frac{\mu_k^2+\left(\pi_k^2\times\left(\frac{\mu_k^2}{\mu_k^2+\nu_k^2}\right)\right)}{\sum_{k=1}^{K}\left(\mu_k^2+\left(\pi_k^2\times\left(\frac{\mu_k^2}{\mu_k^2+\nu_k^2}\right)\right)\right)}, k = 1, 2,..., K. \tag{1}$$

Table 1
Linguistic variables for assessing the importance of the experts [47]

Linguistic variables	Pythagorean fuzzy numbers (μ , ν , π)
Extremely significant (ES)	(0.90, 0.15, 0.409)
Very very significant (VVS)	(0.75, 0.40, 0.527)
Very significant (VS)	(0.60, 0.50, 0.669)
Significant (S)	(0.50, 0.70, 0.592)
Less significant (LS)	(0.40, 0.80, 0.447)
Very less significant (VLS)	(0.30, 0.90, 0.316)

Step 2. Establishing the risk factor importance assessment matrix

In this step, let *j* represent the j^{th} risk factor, where *j* = 1, 2,…, *J*. All experts evaluate the importance of each risk factor based on the linguistic variable table provided in Table 2, thereby establishing the risk factor importance assessment matrix, as shown in Eq. (2).

$$\boldsymbol{A}=\left[a_{jk}\right]_{J\times K}=\begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1k} & \cdots & a_{1K} \\ a_{21} & a_{22} & \cdots & a_{2k} & \cdots & a_{2K} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ a_{j1} & a_{j2} & \cdots & a_{jk} & \cdots & a_{jK} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ a_{J1} & a_{J2} & \cdots & a_{Jk} & \cdots & a_{JK} \end{bmatrix}, j = 1, 2,..., J; k = 1, 2,..., K. \tag{2}$$

where $a_{jk}=\left(a\left(\mu_{jk}\right), a\left(\nu_{jk}\right), a\left(\pi_{jk}\right)\right)$.

Table 2
Linguistic variables for assessing the importance of the risk factors [47]

Linguistic variables	Pythagorean fuzzy numbers (μ , ν , π)
Extremely important (ES)	(0.90, 0.15, 0.409)
Very very important (VVS)	(0.75, 0.40, 0.527)
Very important (VS)	(0.60, 0.50, 0.669)
Important (S)	(0.50, 0.70, 0.592)
Less important (LS)	(0.40, 0.80, 0.447)
Very less important (VLS)	(0.30, 0.90, 0.316)

Step 3. Aggregating the risk factor importance assessment matrix of the group

To generate the group's risk factor importance assessment matrix, the individual judgments of all the experts need to be consolidated into a single group assessment. This is achieved by applying the Pythagorean Fuzzy Weighted Averaging Operator (PFWAO), which effectively combines the individual judgments of the experts into a cohesive group perspective, ensuring that each expert's importance weight is duly considered in the final assessment. In this context, only the membership function and non-membership function need to be utilized, as shown in Eq. (3).

$$q_j = \left(q\left(\mu_j\right), q\left(\nu_j\right)\right) = PFWAO_{w_k^{ex.}}\left(a_{j1}, a_{j2}, ..., a_{jK}\right) = \left(\sqrt{1-\prod_{k=1}^{K}\left(1-\left(a\left(\mu_{jk}\right)\right)^2\right)^{w_k^{ex.}}}, \prod_{k=1}^{K}\left(a\left(\nu_{jk}\right)\right)^{w_k^{ex.}}\right) \quad (3)$$

Step 4. Obtaining the score degrees of the risk factors

To convert Pythagorean fuzzy numbers into crisp values, Eq. (4) is used for the defuzzification process. Then, Eq. (5) is applied to normalize the crisp values to ensure their range is confined within [0, 1].

$$f_j = \left(q\left(\mu_j\right)\right)^2 - \left(q\left(\nu_j\right)\right)^2 \quad (4)$$

$$f_j^* = \frac{1}{2}\left(f_j + 1\right) \quad (5)$$

Step 5. Sorting the score degrees of the risk factors

The obtained score degrees of the risk factors can be sorted from the highest to the lowest, thereby forming a sequence $\left(f^*_{Sorting\_1}, f^*_{Sorting\_2}, ..., f^*_{Sorting\_j}, ..., f^*_{Sorting\_K}\right)$.

Step 6. Calculating the relative coefficients of the risk factors

The relative coefficients of the risk factors are calculated using Eq. (6).

$$\partial_{Sorting\_j} = \begin{cases} 1, & \text{for } Sorting\_j = 1 \\ 1 + \left(f^*_{Sorting\_j-1} - f^*_{Sorting\_j}\right), & \text{for } Sorting\_j = 2 \sim K \end{cases} \quad (6)$$

Step 7. Calculating the weights of the risk factors

The weights of the risk factors can be derived through calculations using Eq. (7) and Eq. (8).

$$\eta_{Sorting\_j} = \begin{cases} 1, & \text{for } Sorting\_j = 1 \\ \dfrac{\eta_{Sorting\_j-1}}{\partial_{Sorting\_j}}, & \text{for } Sorting\_j = 2 \sim K \end{cases} \quad (7)$$

$$w^{RF}_{Sorting\_j} = \frac{\eta_{Sorting\_j}}{\sum_{Sorting\_j=1}^{Sorting\_K} \eta_{Sorting\_j}} \quad (8)$$

3.2 PF-TOPSIS

The TOPSIS technique is primarily utilized to identify the Positive Ideal Solution (PIS) and Negative Ideal Solution (NIS) among many assessed items, aiming to determine the relative position of each item. This determination is achieved by calculating the distances between each item and the PIS and NIS, with the optimal item being the one closest to the PIS and farthest from the NIS [48]. TOPSIS has been widely applied in performance evaluation problems, such as sustainable cities and communities assessment [49], green low-carbon port evaluation [50], software requirements selection [51]. This study integrated Pythagorean fuzzy sets with TOPSIS, and enhanced practicality of TOPSIS by the new ranking index proposed by Kuo [52], is leveraged to achieve a more accurate ranking. The steps for PF-TOPSIS are outlined as follows:

Step 1. Constructing the risk assessment matrix

PF-TOPSIS builds upon the framework established by PF-SWARA, where *k* denotes the k^{th} expert, and *k* = 1, 2,…, *K*; *j* denotes the j^{th} risk factor, where *j* = 1, 2,…, *J*; and *i* denotes the i^{th} supplier, where *i* = 1, 2,…, *I*. Expert *k* is tasked with assessing the risk level of supplier *i* under risk factor *j*, leading to the creation of the risk assessment matrix as shown in Eq. (9). The linguistic variables referred to are detailed in Table 3.

$$\boldsymbol{D}=\left[d_{ij}^{(k)}\right]_{I\times J}=\begin{bmatrix} \left\{d_{11}^{(1)}, d_{11}^{(2)},\dots, d_{11}^{(K)}\right\} & \left\{d_{12}^{(1)}, d_{12}^{(2)},\dots, d_{12}^{(K)}\right\} & \cdots & \left\{d_{1j}^{(1)}, d_{1j}^{(2)},\dots, d_{1j}^{(K)}\right\} & \cdots & \left\{d_{1J}^{(1)}, d_{1J}^{(2)},\dots, d_{1J}^{(K)}\right\} \\ \left\{d_{21}^{(1)}, d_{21}^{(2)},\dots, d_{21}^{(K)}\right\} & \left\{d_{22}^{(1)}, d_{22}^{(2)},\dots, d_{22}^{(K)}\right\} & \cdots & \left\{d_{2j}^{(1)}, d_{2j}^{(2)},\dots, d_{2j}^{(K)}\right\} & \cdots & \left\{d_{2J}^{(1)}, d_{2J}^{(2)},\dots, d_{2J}^{(K)}\right\} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ \left\{d_{i1}^{(1)}, d_{i1}^{(2)},\dots, d_{i1}^{(K)}\right\} & \left\{d_{i2}^{(1)}, d_{i2}^{(2)},\dots, d_{i2}^{(K)}\right\} & \cdots & \left\{d_{ij}^{(1)}, d_{ij}^{(2)},\dots, d_{ij}^{(K)}\right\} & \cdots & \left\{d_{iJ}^{(1)}, d_{iJ}^{(2)},\dots, d_{iJ}^{(K)}\right\} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ \left\{d_{I1}^{(1)}, d_{I1}^{(2)},\dots, d_{I1}^{(K)}\right\} & \left\{d_{I2}^{(1)}, d_{I2}^{(2)},\dots, d_{I2}^{(K)}\right\} & \cdots & \left\{d_{Ij}^{(1)}, d_{Ij}^{(2)},\dots, d_{Ij}^{(K)}\right\} & \cdots & \left\{d_{IJ}^{(1)}, d_{IJ}^{(2)},\dots, d_{IJ}^{(K)}\right\} \end{bmatrix}$$

$$,i = 1, 2,\dots, I;\ j = 1, 2,\dots, J;\ k = 1, 2,\dots, K. \tag{9}$$

where $d_{ij}^{(k)}=\left(d\left(\mu_{ij}^{(k)}\right), d\left(\nu_{ij}^{(k)}\right), d\left(\pi_{ij}^{(k)}\right)\right)$.

Table 3
Linguistic variables for assessing the risk rating of the suppliers [47]

Linguistic variables	Pythagorean fuzzy numbers (μ , ν , π)
Always occurs (ES)	(0.90, 0.15, 0.409)
Highly likely (VVS)	(0.75, 0.40, 0.527)
Moderate (VS)	(0.60, 0.50, 0.669)
Low (S)	(0.50, 0.70, 0.592)
Slight (LS)	(0.40, 0.80, 0.447)
Never occurs (VLS)	(0.30, 0.90, 0.316)

It’s particularly noteworthy that, in this context, the highest and lowest risk ratings are treated as if they were two suppliers. This approach enables us to identify the sets of highest and lowest risks. By conceptualizing these extremities as suppliers, we can effectively gauge the range of risk within the assessment, providing a clear delineation of the spectrum of risk exposure faced by the organization.

Step 2. Aggregating the risk assessment matrix of the group and the risk score degree matrix

This step mirrors Steps 3 and 4 of the PF-SWARA method, employing Eq. (3)-(5) to aggregate the experts’ judgments and perform defuzzification, thereby obtaining the group’s risk assessment matrix and the risk score degree matrix, as shown in Eq. (10) and Eq. (11), respectively. This process not only consolidates the diverse opinions of the experts into a unified assessment but also translates the fuzzy evaluations into crisp scores, facilitating a clearer and more actionable understanding of each risk factor’s relative importance and impact on the study’s focus area.

$$\boldsymbol{P} = \left[p_{ij} \right]_{I \times J} = \begin{bmatrix} p_{11} & p_{12} & \cdots & p_{1j} & \cdots & p_{1J} \\ p_{21} & p_{22} & \cdots & p_{2j} & \cdots & p_{2J} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ p_{i1} & p_{i2} & \cdots & p_{ij} & \cdots & p_{iJ} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ p_{I1} & p_{I2} & \cdots & p_{Ij} & \cdots & p_{IJ} \end{bmatrix}, \; i = 1, 2, \ldots, I; \; j = 1, 2, \ldots, J. \tag{10}$$

where $p_{ij} = \left(p\left(\mu_{ij}\right), p\left(\nu_{ij}\right), p\left(\pi_{ij}\right) \right)$.

$$\boldsymbol{S} = \left[s_{ij} \right]_{I \times J} = \begin{bmatrix} s_{11} & s_{12} & \cdots & s_{1j} & \cdots & s_{1J} \\ s_{21} & s_{22} & \cdots & s_{2j} & \cdots & s_{2J} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ s_{i1} & s_{i2} & \cdots & s_{ij} & \cdots & s_{iJ} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ s_{I1} & s_{I2} & \cdots & s_{Ij} & \cdots & s_{IJ} \end{bmatrix}, \; i = 1, 2, \ldots, I; \; j = 1, 2, \ldots, J. \tag{11}$$

Step 3. Obtaining the weighted normalized risk matrix

By applying the risk factor weights obtained from the PF-SWARA method to the risk score degree matrix, the weighted normalized risk matrix can be derived, as detailed in Eq. (12).

$$\boldsymbol{X} = \left[x_{ij} \right]_{I \times J} = \left[\left(w_j \right) \cdot s_{ij} \right]_{I \times J}, \; i = 1, 2, \ldots, I; \; j = 1, 2, \ldots, J. \tag{12}$$

Step 4. Identifying the PIS and NIS

In this context, the PIS ($z^{+} = \left\{ z_1^{+}, z_2^{+}, \ldots, z_j^{+}, \ldots, z_J^{+} \right\}$) is defined as the set of the highest risk ratings, indicating the least favorable or worst-case scenario. Conversely, the NIS ($z^{-} = \left\{ z_1^{-}, z_2^{-}, \ldots, z_j^{-}, \ldots, z_J^{-} \right\}$) is identified as the set of the lowest risk ratings, representing the most favorable or optimal scenario regarding risk management. This refers to the two hypothetical suppliers that were specifically added in Step 1 of the PF-TOPSIS process.

Step 5. Calculating the respective separation distances of suppliers from the PIS and NIS

The suppliers were ranked based on separation distance, with the PIS distance for suppliers referred to as D^{+} (Eq. (13)) and the NIS distance referred to as D^{-} **(**Eq. (14)).

$$D_i^{+} = \sqrt{\sum_{j=1}^{J} \left(x_{ij} - z^{+} \right)^2}, \; i = 1, 2, \ldots, I. \tag{13}$$

$$D_i^{-} = \sqrt{\sum_{j=1}^{J} \left(x_{ij} - z^{-} \right)^2}, \; i = 1, 2, \ldots, I. \tag{14}$$

Step 6. Calculating the risk ranking index

The risk ranking index can serve as the final risk score for suppliers, with its calculation detailed in Eq. (15).

$$RI_i = \alpha \left(\frac{D_i^{-}}{\sum_{i=1}^{I} D_i^{-}} \right) - \left(1 - \alpha\right) \left(\frac{D_i^{+}}{\sum_{i=1}^{I} D_i^{+}} \right), \; -1 \le RI_i \le 1. \tag{15}$$

4. Data demonstration

This section outlines the background of the case study and the data collection process. It is followed by the data analysis based on the computational procedures presented in Section 3.

4.1 Background description and data collection

The machine tool industry in Taiwan is characterized by several unique features, including a pronounced clustering phenomenon and a high capability for customization. Predominantly located in the central region, this industry benefits from a well-developed supply system and a significant reliance on international trade. This study focuses attention on a multinational machine tool manufacturing company as the main object of analysis. The company in focus primarily produces rotary tables, a crucial mechanism for machining aerospace and medical parts, typically integrated within computer numerical control (CNC) machining centers.

This study involved a team of eight highly experienced experts from the company, including the directors of Factory A and Factory B, the manager and assistant manager of the procurement department, and four supplier audit engineers. All of these experts were highly familiar with the supply chain conditions of the machine tool industry and possessed many years of work experience. Information on the background of these eight experts is presented in Table 4. The eight experts were first familiarized with the meaning of the eight disruption risk factors. They then learned how to complete the PF-SWARA and PF-TOPSIS questionnaires, which were distributed and collected over the course of one month. Throughout this time, the experts utilized their expertise to provide responses based on past procurement data or surveys conducted at the supplier's site.

Table 4

The background of the eight experts

Expert	Department	Title	Years of Experience	Education
No. 1	Factory A	Director	Over 20 years	Ph. D.
No. 2	Factory B	Director	Over 20 years	Ph. D.
No. 3	Procurement department	Manager	Over 20 years	Ph. D.
No. 4	Procurement department	Assistant manager	10 to 20 years	Master
No. 5	Procurement department	Supplier audit engineer	Over 20 years	Master
No. 6	Procurement department	Supplier audit engineer	10 to 20 years	Ph. D.
No. 7	Procurement department	Supplier audit engineer	5 to 10 years	Master
No. 8	Procurement department	Supplier audit engineer	5 to 10 years	Master

The importance ratings given by the eight experts are shown in Table 5. For instance, expert No. 1 rated the importance as "extremely significant (ES)," which translates to Pythagorean fuzzy numbers (0.90, 0.15, 0.409). Through the calculation of importance, the weights of the experts can be obtained. Experts No. 1 and No. 2 weigh 0.155, Experts No. 3 through No. 6 weigh 0.123 each, and Experts 7 and No. 8 weigh 0.099.

Table 5
The weights of the eight experts

Expert	Linguistic variable	Pythagorean fuzzy numbers	Expert weight
No. 1	Extremely significant (ES)	(0.90, 0.15, 0.409)	0.155
No. 2	Extremely significant (ES)	(0.90, 0.15, 0.409)	0.155
No. 3	Very very significant (VVS)	(0.75, 0.40, 0.527)	0.123
No. 4	Very very significant (VVS)	(0.75, 0.40, 0.527)	0.123
No. 5	Very very significant (VVS)	(0.75, 0.40, 0.527)	0.123
No. 6	Very very significant (VVS)	(0.75, 0.40, 0.527)	0.123
No. 7	Very significant (VS)	(0.60, 0.50, 0.669)	0.099
No. 8	Very significant (VS)	(0.60, 0.50, 0.669)	0.099

4.2. Using PF–SWARA to determine the weights of risk factors

Following the PF-SWARA calculation procedure introduced in Section 3.1, the eight experts were asked to assess the importance of eight risk factors, resulting in Table 6. For example, Expert No. 1 considered the importance of R_1 (here, the risk factor is denoted by "R") to be "low (S)." Similarly, the importance of each element can be derived in this manner, providing a structured way to quantify the perspectives of the experts on the relative importance of each risk factor in the analysis.

Table 6
The risk factor importance assessment matrix

Risk factor	Expert No. 1	Expert No. 2	Expert No. 3	Expert No. 4	Expert No. 5	Expert No. 6	Expert No. 7	Expert No. 8
R_1	S	S	S	S	LS	S	LS	S
R_2	VVS	VVS	VVS	VS	S	VVS	LS	VVS
R_3	LS	S	S	S	LS	S	LS	S
R_4	ES	VVS	VS	VS	S	VVS	S	VS
R_5	ES	VVS	ES	VS	S	VVS	S	VVS
R_6	VS	S	VS	VS	S	VS	LS	S
R_7	VS	S	VS	VS	VS	VS	LS	S
R_8	ES	ES	ES	ES	ES	ES	ES	ES

Table 7 showcases the analysis results of the PF-SWARA analysis, revealing that the highest weight is assigned to R_8, indicating it as the most significant risk factor, while R_3 is identified as the least important risk factor. Overall, the importance of the risk factors is ranked as follows: R_8, R_5, R_4, R_2, R_7, R_6, R_1, and R_3, providing a clear hierarchy of concerns that need to be addressed within the context of the study.

Table 7
The results of the PF–SWARA analysis

Risk factor	Weight	Rank
R_1	0.1003	7
R_2	0.1297	4
R_3	0.0985	8
R_4	0.1345	3
R_5	0.1436	2
R_6	0.1122	6
R_7	0.1145	5
R_8	0.1668	1

4.3. Using PF-TOPSIS to calculate the risk score of the suppliers

Following the implementation steps of PF-TOPSIS mentioned in Section 3.2, the risk ranking index for suppliers can be calculated. In this case study, the case company has 22 key suppliers, denoted by the symbol "*S*", with the highest and lowest risk levels included as the 23rd and 24th suppliers, respectively. Through a thorough investigation, all suppliers' rating data can be obtained. After applying Steps 1 and 2 of the PF-TOPSIS, the risk score degree matrix can be derived, which is shown in Table 8.

Table 8
The risk score degree matrix

Risk factor	R_1	R_2	R_3	R_4	R_5	R_6	R_7	R_8
Weight	0.1003	0.1297	0.0985	0.1345	0.1436	0.1122	0.1145	0.1668
S_1	0.2959	0.3082	0.3082	0.1879	0.3082	0.3082	0.4567	0.2959
S_2	0.2959	0.2202	0.4134	0.3082	0.5947	0.3082	0.1879	0.2959
S_3	0.2959	0.3082	0.3082	0.4567	0.3082	0.4454	0.3082	0.1941
S_4	0.2959	0.3082	0.3082	0.6171	0.3082	0.4454	0.3082	0.5657
S_5	0.2959	0.3082	0.4134	0.3082	0.3082	0.2029	0.3082	0.2959
S_6	0.4454	0.5941	0.3377	0.3377	0.3231	0.3231	0.2174	0.3377
S_7	0.2347	0.3377	0.2483	0.3377	0.4679	0.4679	0.6529	0.3377
S_8	0.2486	0.3519	0.3519	0.2316	0.3377	0.3377	0.3519	0.6397
S_9	0.3377	0.3519	0.3519	0.3519	0.3377	0.3377	0.2316	0.3519
S_{10}	0.3377	0.3519	0.3519	0.2316	0.3377	0.3377	0.3519	0.4992
S_{11}	0.3377	0.3519	0.2618	0.3519	0.3377	0.3377	0.5185	0.6397
S_{12}	0.3260	0.4827	0.3519	0.3519	0.4890	0.2316	0.3519	0.2374
S_{13}	0.3260	0.4827	0.2618	0.3519	0.3377	0.2316	0.3519	0.3405
S_{14}	0.3260	0.3519	0.6136	0.3519	0.3377	0.4890	0.5185	0.3405
S_{15}	0.3260	0.2618	0.4827	0.3519	0.4890	0.3377	0.3519	0.3405
S_{16}	0.3260	0.3519	0.3519	0.3519	0.3377	0.2316	0.5185	0.3405
S_{17}	0.3260	0.3519	0.2618	0.5185	0.3377	0.3377	0.5185	0.6252
S_{18}	0.3112	0.4611	0.4611	0.3377	0.4679	0.2174	0.3377	0.3260
S_{19}	0.2959	0.2202	0.3082	0.1879	0.3082	0.3082	0.3082	0.5657
S_{20}	0.4009	0.3082	0.3082	0.4567	0.3082	0.3082	0.3082	0.2959
S_{21}	0.2959	0.2202	0.3082	0.3082	0.2029	0.4454	0.3082	0.2959
S_{22}	0.5397	0.5521	0.4134	0.3082	0.3082	0.3082	0.3082	0.5657
S_{23} (the highest risk rating)	0.8938	0.8938	0.8938	0.8938	0.8938	0.8938	0.8938	0.8938
S_{24} (the lowest risk rating)	0.1400	0.1400	0.1400	0.1400	0.1400	0.1400	0.1400	0.1400

Table 9
The results of the PF–TOPSIS analysis

	D^+	D^-	Risk ranking index	Rank
S_1	0.2134	0.0630	-0.0089	20
S_2	0.2057	0.0832	-0.0034	15
S_3	0.2094	0.0708	-0.0066	19
S_4	0.1765	0.1108	0.0062	2*
S_5	0.2129	0.0603	-0.0094	21
S_6	0.1937	0.0881	-0.0009	8
S_7	0.1860	0.0984	0.0023	7*
S_8	0.1892	0.1015	0.0027	5*
S_9	0.2010	0.0711	-0.0056	18
S_{10}	0.1931	0.0849	-0.0016	11
S_{11}	0.1765	0.1106	0.0062	4*

	D^+	D^-	Risk ranking index	Rank
S_{12}	0.1974	0.0839	-0.0023	12
S_{13}	0.1988	0.0768	-0.0041	16
S_{14}	0.1818	0.0971	0.0025	6*
S_{15}	0.1912	0.0852	-0.0013	10
S_{16}	0.1964	0.0791	-0.0033	14
S_{17}	0.1695	0.1165	0.0083	1*
S_{18}	0.1910	0.0866	-0.0009	9
S_{19}	0.2060	0.0838	-0.0032	13
S_{20}	0.2020	0.0724	-0.0054	17
S_{21}	0.2181	0.0587	-0.0104	22
S_{22}	0.1747	0.1098	0.0062	3*
S_{23} (the highest risk rating)	0.0000	0.2705	0.0625	
S_{24} (the lowest risk rating)	0.2705	0.0000	-0.0297	

Table 9 presents the results of the PF-TOPSIS analysis and shows that S_{17} poses the highest risk among the suppliers. Seven suppliers, including S_{17}, S_4, S_{22}, S_{11}, S_8, S_{14}, and S_7, have a risk ranking index greater than 0. Therefore, it is important to pay closer attention to these seven suppliers, while the rest of the case company's suppliers have relatively low disruption risks. This analysis confirms that the supply chain of the case company is highly robust, with only a handful of suppliers identified as potential risk points. By focusing on these seven suppliers, targeted risk management strategies can be implemented to effectively mitigate potential disruptions and enhance overall supply chain resilience. Suggested measures for improvement and recommendations are provided in the discussion section below.

4. Discussion and Conclusions

In this case study, "Natural Disasters and Geopolitical Risks (R_8)" is identified as the most critical risk factor (w_8 = 0.1668) impacting the supply chain of the machine tool manufacturing industry. This is primarily due to the industry's unique vulnerabilities, with the concentration of manufacturing facilities and suppliers in Taiwan, a region prone to typhoons and earthquakes, amplifying the risk of disruptions caused by natural disasters. The industry's key players are geographically clustered, which promotes efficiency and collaboration. However, this clustering also exposes them to the risk of simultaneous operational disruptions. Furthermore, the industry's dependency on a global supply chain for raw materials, components, and access to export markets leads to substantial vulnerability to geopolitical risks. Trade tensions, tariffs, and sanctions can quickly alter trade routes, increase costs, and restrict access to vital markets and supplies, highlighting the delicate balance of international relations.

The machine tool industry's demand for high customization and precision exacerbates the supply chain's sensitivity to disruptions. The reliance on specialized suppliers means that any disruption, whether from natural disasters or geopolitical issues, can significantly delay production processes, affecting the timely delivery of customized and precise machinery. Implementing lean manufacturing practices is a common strategy in this sector for reducing costs by minimizing inventory. However, it also further narrows the margin for error or delay, which can rapidly result in shortages and stalling production lines due to the lack of buffer inventory. It is important to note that Taiwan's central region is a strategically important industry hub, but it also presents both an asset and a liability. The region's vulnerability to natural disasters, combined with its geopolitical sensitivity, particularly in the Asia-Pacific region, adds additional risk to the supply chain. This strategic geographic location not only exposes the industry to natural disaster risks but also to geopolitical tensions that threaten supply chain stability and security.

"Financial Instability (R_5)" ranks as the second most important risk factor in this case study (w_5 = 0.1436), largely due to the interconnected nature of the global economy and its impacts on the machine tool manufacturing industry's supply chain. The industry's exposure to rising inflation has dramatically increased costs for raw materials and logistics, placing a significant financial strain on suppliers. This can lead to reduced operational capacity, delayed innovations, or even complete shutdowns, directly threatening the continuity of the supply chain. The industry's complex, global supply chain further amplifies this risk, as financial instability can prevent key suppliers from timely delivering essential components, causing production delays. Additionally, financial challenges can force suppliers to compromise on quality or extend payment terms, disrupting both supply chain operations and product integrity. Compounded by the effects of global inflation, such as tighter credit markets, suppliers find it increasingly difficult to secure the financing they need to remain competitive and operationally efficient. Moreover, the resulting cost increases can be passed on to manufacturers, impacting the industry's cost structure and squeezing profit margins. These dynamics underscore the need for robust financial risk management strategies to navigate the challenges posed by financial instability within the supply chain.

"Delivery Delays (R_4)", the third major risk factor (w_4 = 0.1345), is intricately linked to "Natural Disasters and Geopolitical Risks (R_8)" and "Financial Instability (R_5)," showing the complex interdependencies within the machine tool manufacturing industry's supply chain. Natural disasters can disrupt logistics and transportation, while geopolitical tensions can create trade barriers, both of which can lead to significant delivery delays. These issues can be compounded when suppliers face financial instability that affects their ability to maintain inventory or manage timely order fulfillment, especially during economic downturns. This interconnectedness underscores the need for an integrated risk management approach, as disruptions in one area can trigger widespread impacts. This underlines the importance of strategic planning to mitigate the combined impact of these risk factors on the supply chain.

Table 9 shows the results of the PF-TOPSIS evaluation. Seven suppliers, namely S_{17}, S_4, S_{22}, S_{11}, S_8, S_{14}, and S_7, have a Risk Ranking Index greater than 0. For these seven suppliers, it is necessary to mitigate the occurrence of the following three disruption risks: "Natural Disasters and Geopolitical Risks (R_8)," "Financial Instability (R_5)," and "Delivery Delays (R_4)."

To mitigate the disruption risks effectively, diversifying supply sources and reducing reliance on vulnerable regions or suppliers is necessary. This buffers against disruptions caused by natural or geopolitical events. Maintaining strategic reserves of critical components and implementing flexible manufacturing systems enhances the ability to adapt to sudden changes in supply availability. Regular assessments of geopolitical risks and the financial health of suppliers enable early identification of potential issues. This enables the development of contingency plans and support programs to stabilize the supply chain.

Incorporating risk-sharing clauses in contracts can reduce the impact of financial instability while developing alternative suppliers ensures there are backup options for critical components. Improving the accuracy of forecasts and collaborative planning with suppliers can help to align expectations and identify potential delays early. Implementing performance-based incentives can encourage suppliers to adhere to delivery schedules, and investing in supply chain visibility tools can provide real-time tracking capabilities and improve overall supply chain responsiveness. The adoption of these measures requires a balanced consideration of cost and practicality, emphasizing the need for regular review and adaptation to effectively manage and respond to evolving supply chain risks, thereby ensuring resilience and stability.

This study marks a significant advancement in the field of risk management in the machine tool manufacturing industry. It comprehensively analyzes eight potential disruption risk factors and employs the Pythagorean fuzzy SWARA-TOPSIS approach for the first time to evaluate supplier disruption risks. The assessment process values expert opinions and tackling uncertainties, resulting in a thorough and nuanced evaluation. Furthermore, the study provides targeted improvement recommendations for suppliers at higher disruption risks, practical solutions for mitigating these risks, and ways to bolster supply chain resilience. This holistic approach not only enhances understanding of supply chain vulnerabilities but also provides actionable insights for strengthening industry practices.

While this study introduces a novel conceptual model for risk management in the machine tool manufacturing industry, it is important to acknowledge certain limitations that necessitate further exploration. One such limitation is the absence of a detailed discussion on the interrelationships among the eight identified risk factors. This omission restricts our ability to fully elucidate the primary causes of these risks and identify which factors are most susceptible to influence. On another note, the field of fuzzy logic offers a plethora of variant theories that hold potential for future research applications. These alternative fuzzy methodologies may provide more nuanced insights or more robust frameworks for assessing and mitigating risks within the supply chain. Exploring these variant fuzzy theories could enhance the model's effectiveness in predicting and managing risks, thereby contributing to a deeper understanding and more sophisticated approaches to risk management in the machine tool manufacturing sector.

Future studies could benefit from incorporating a comprehensive analysis of risk interdependencies, employing advanced fuzzy logic techniques and influential relationship identification methods to model these relationships accurately. Moreover, investigating the applicability and impact of various fuzzy methodologies could reveal innovative strategies for risk assessment, offering valuable contributions to both theoretical frameworks and practical applications in risk management.

Author Contributions

Conceptualization, Ling-Yu Wang and Adam Kao-Wen Weng; methodology, Huai-Wei Lo; software, Huai-Wei Lo; validation, Ling-Yu Wang and Adam Kao-Wen Weng and Sheng-Wei Lin; formal analysis, Ling-Yu Wang and Adam Kao-Wen Weng and Sheng-Wei Lin; investigation, Ling-Yu Wang and Adam Kao-Wen Weng; resources, Huai-Wei Lo; data curation, Huai-Wei Lo; writing—original draft preparation, Sheng-Wei Lin; writing—review and editing, Huai-Wei Lo; visualization, Ling-Yu Wang and Adam Kao-Wen Weng; supervision, Sheng-Wei Lin; project administration, Huai-Wei Lo. All authors have read and agreed to the published version of the manuscript.

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There is no data in this study.

Conflicts of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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