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Fuzzy-Based Bow-Tie Framework for Supply Chain Risk Assessment of Restaurant Delivery Service

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Abstract. Supply chain and supply chain management start from the procurement of raw materials from the manufacturer to the consumption of the final product by the consumer. Restaurants generally require a simple but strict sequential supply chain. To satisfy customer expectations, restaurants must anticipate and manage potential risks, that is, supply, operational, demand, and macro risks. There are many factors for each potential risk that can cause these disruptions. An effective risk assessment for restaurant delivery services is still a gap that needs to be filled as a risk analysis, and their impact on customer satisfaction is often imprecise or vague due to linguistic uncertainties. This study proposes a fuzzy-based bowtie framework to improve risk assessment for the supply chain by eliminating these linguistic variations. Potential risks and risk factors were systematically identified and categorized throughout the study. A sensitivity analysis was also carried out to identify and determine significant risk factors and their contributions to the proposed framework to improve risk management. The results prove that eliminating the risk factor with the highest deviation will result in an improvement in the risk management of the restaurant supply chain.

Key-words: Fuzzy-based bow-tie framework; risk assessment; sensitivity analysis; supply chain.

1. Introduction

Risk consequences adversely affect the activities involved in production or operations. These are usually unforeseen situations that result in deviations from the expected goals or objectives. Identifying risks before they occur to avoid their consequences is a complex study at the operational level. A supply chain starts with the procurement of raw materials from the manufacturer to the consumption of the final product by the consumer. It is an integrated system that includes the manufacturer, vendors, wholesalers, retailers, and consumers as well as production and logistics activities. A successful supply chain synchronizes all its processes by encouraging a smooth flow of information and materials to all members involved [1], [2]. However, risks can occur at any point and are unforeseen events that can lead to partial or complete disruption of the supply chain. Most supply chains are sequential, that is, the next stage cannot begin until the previous stage is complete. Therefore, if a disruptive risk event occurs at any stage, it has a negative effect on the supply chain [3], [4]. Supply chain risk and supply chain risk management (SCRM) are currently being studied together as systems. Supply chain risks can arise from different environmental, internal, or external factors, which can be difficult to identify. These factors that affect the supply chain can lead to unwanted outcomes, either disrupting the original operational plan or resulting in undesirable goods to the consumer [5], [6]. Hence, the necessity of risk management has been raised to pose potential risks that affect supply chain activities. SCRM is a process or system that companies can use to mitigate or eliminate risks that would have negative effects on the supply chain. Synchronizing risk-management efforts is essential to avoid disrupting supply chain activities. The importance of SCRM cannot be overemphasized because a single disruption in activities can break down a supply chain, cause loss of investment, loss of trust between partners, delay in delivery, and ultimately unsatisfied customers [5]–[8]. This is why supply chain risk management is important, and all parties involved in the supply chain should collaborate to mitigate and eliminate potential risks. Restaurants generally require simple but strict sequential supply chains. Most restaurants receive orders and prepare them according to the customer specifications. This requires restaurant management to know their customers' order variety and the ingredients that need to be provided by suppliers ahead of time. Many studies have examined how to mitigate risks and increase customer satisfaction in the food supply chain industry, but very few have focused on restaurant delivery services. In [9], the effect of perceived risk on customer satisfaction at restaurants during October 2021 was investigated using the snowball sampling technique. The authors focused on several factors for perceived risks, namely security factors such as financial risk, psychological risk, and physical risk. A questionnaire was distributed online for data collection via Google Form, and the data were analyzed using partial least squares structural equation modeling (PLS-SEM). The results indicate that perceived risk has no negative effect on customer satisfaction. The authors in [10] aimed to analyze customer satisfaction by introducing an integrated structural model that combines the service quality dimensions of food and employee service quality, timeliness, aesthetics, facility comfort, and cleanliness. A six-dimensional service quality scale was used to collect data from 309 customers who received services from a particular restaurant. Path analysis was applied to examine the relationships among service quality, perceived value, and customer satisfaction. The authors observed that service quality and other dimensions, except aesthetics, had a positive effect on customer satisfaction. On the other hand, a multi-layer/multidimensional approach was applied in [11] with a hierarchical framework to examine the level of customer satisfaction by focusing on dimensions such as customer behavior, which includes two dimensions: participation behavior and citizenship behavior. The authors also considered customer-perceived values in three dimensions: economic, individual, and relational. Qualitative analysis was used to analyze the dining experiences of 514 customers. The findings show that a customer's perception of value has a greater impact on citizenship behavior than on participation behavior. The studies in the literature which are focused on restaurant delivery service, are mainly based on qualitative data analysis to examine perceived risks and customers' satisfaction; hence, the risk analysis and their impacts on customers' satisfactions are often imprecise or vague due to linguistic uncertainties. Therefore, an effective risk assessment for restaurant delivery service is still a gap that is necessary to be filled.

In this study, a fuzzy-based framework with bow-tie analysis for the supply chain risk assessment of a restaurant delivery service is proposed using both qualitative and quantitative techniques. For this purpose, the opinions of experts were collected via interviews to identify risk factors and their impacts on this sector. Experts were more comfortable expressing their opinions in terms of linguistic expressions than numerical values. Hence, the motivation of this study is to eliminate the vagueness of experts' opinions due to their linguistic variations by adopting a fuzzy-based approach with bow-tie analysis, which is a comprehensive risk assessment approach, to link sources of risk and consequences in an effective way. Herewith, the fuzzy-based framework is adopted to overcome linguistic uncertainties of experts' opinions with bow-tie analysis, which is used to calculate the aggregated risk probability and their impacts. The potential risks posed to the restaurant supply chain and their implications were systematically identified and categorized using literature review and expert opinions (restaurant owners, chiefs, etc.). Main contribution of this study is to identify the most significant risk factors in the supply chain of food delivery services in restaurants through the proposed risk assessment approach. And, to perform a sensitivity analysis to mitigate the potential risks and assess the variations in risk probability by eliminating a particular risk factor to improve the risk management process. The remainder of this paper is organized as follows. Section 2 provides information on the SCRM strategies developed for risk mitigation to improve supply chain performance. The proposed framework and applied methodology are presented in Section 3. Section 4 presents the data analysis. The findings and discussion are given in Section 5, and the article is concluded in Section 6.

2. Literature Review

SCRM is an emerging topic with growing concerns due to increasing supply chain risks. It has also attracted the attention of researchers as it is an effective approach that can be used in the service and manufacturing industries in terms of solving and mitigating potential risks. In addition, uncertainties increase as risks increase, and these uncertainties are the primary factors of any risk assessment process. Because of their nature, risks can never be eliminated completely. However, an appropriate supply chain risk assessment approach is required to mitigate the effects of risks to an acceptable level [12]–[15]. Several studies have comprehensively reviewed and synthesized the extant literature on SCRM [1], [2], [4], [16], [17]. Such studies performed a systematic literature review on SCRM to identify strategies developed to mitigate risks and improve supply chain performance. The authors stated that there is heterogeneity in the strategies developed to mitigate supply chain risks, such as simulation/modeling and quantitative and qualitative methods. The detailed literature review is given in [23], and the references cited in [23] respect the list given in the References section of this paper.

3. Proposed Framework

In this study, a simple three-party supply chain model was considered a food delivery service for restaurants. It consists of a supplier that brings the raw materials to be processed, a service provider (which is a restaurant cuisine system), and a customer who asks for a service. The flow of the supply chain model is in sequential order as supplier, service provider, and customer. Third-party logistics and intersectional distributions are eliminated to simplify the model. Figure 3, given in [23], shows the proposed food delivery service for a restaurant with all the considered risks that may affect its supply chain. The proposed framework focuses on fuzzy-based bow-tie analysis for effective risk management in food delivery services in a restaurant supply chain. Figure 4, given in [23], illustrates the conceptual framework of this research. As shown in the figure, the risk event (R_i) and risk factors (F_{ij}) of each risk were identified through surveys and data collection from experts via interviews. It is worth mentioning that each risk event has various risk factors and impacts on the supply chain. Interviews were conducted with three volunteer experts at three different restaurants. Open-ended interview questions were used to collect the opinions of experts from the perspective of the obtained risk factors, as well as the impacts related to each risk. Examples of the interview questions are as follows, but not limited to: "What are the problems that you are facing when ordering raw materials from the suppliers?", "What are the difficulties that you are facing related to customers' orders?", "Could you please explain the factors that cause difficulties during preparation of customers' orders? "What kind of risks do you have at your restaurant cuisine?", "What do you think about uncontrollable problems or risks that may affect the food delivery service of your restaurant?" Based on the interview data, the risk impacts were categorized for each risk factor. In this context, the opinions of the experts were asked about impacts of these risk factors. Table 1, presented in [23], presents the opinions of experts by means of the emerged risk impact. Additionally, Table 2 in [23] shows all risk factors and impacts related to each risk, which were obtained and categorized based on literature research and interviews with experts. The experts stated their opinions on the effect of identified risk factors and their impacts on their restaurant's food delivery service via interviews. Due to linguistic variabilities, accurate estimations of the probability of occurrence (or likelihood) of the risk factor and impact values are often imprecise or vague. However, experts are more comfortable expressing their opinions in terms of linguistic expressions than numerical values. Hence, the fuzzy-based approach is adopted in the proposed framework using triangular fuzzy numbers (TFNs) to define the occurrence probability as the input data. Membership functions characterize fuzziness with a fuzzy set in which each data is assigned a membership grade ranging between 0 and 1. TFNs are defined as the lower, mid, and upper boundaries that describe a fuzzy number. Note that the lower and upper boundaries for each linguistic grade can vary according to the defined system [26], [39], [40]. Linguistic variables and associated fuzzy numbers were adopted from [34] to quantify linguistic expert opinions concerning risk likelihood and risk impact as in Table 3 given in [23]. In the proposed framework, linguistic variations are categorized into five linguistic grades: risk factor scale: Expected, Possible, Unlikely, Very unlikely, Not expected, and risk impact scale: High, Medium, Low, Very Low, None. Table 3, given in [23], shows the associated fuzzy numbers, which were used to quantify the linguistic uncertainty of experts' opinions. Tables 4 and 5, given in [23], show the experts' opinions in terms of linguistic grades. It is worth mentioning that the risk impacts in Table 5 given in [23] are also divided into two subcategories: risk impacts and their associated probabilities. As shown in the flowchart of the proposed framework in Figure 4, linguistic uncertainties due to the variations in experts' opinions must be eliminated after evaluations of the identified risk factors and impacts. Hence, the fuzzy analytic hierarchical process (AHP) method was used to perform the linguistic assessment of risk likelihood. The obtained fuzzy numbers were then used to perform risk analysis via the bow-tie method to obtain the probability and impact score for the risk event. To perform bowtie analysis with a fault tree and event tree, which show the causes and consequences of a risk event, respectively. Figure 5, given in [23], illustrates the flowchart of the detailed bow-tie with all the identified risk factors, risk events, and risk impacts for the proposed framework. Furthermore, defuzzification was applied to obtain crisp numbers for the scores obtained. The defuzzified numbers were then ranked using the risk priority matrix (RPM) to perform a sensitivity analysis for the identification of significant risk factors and improve risk management. In the proposed framework, the logical OR gate was used to represent the relationship between the risk factors, as any risk factor can cause a risk event. Figure 6 given in [23] illustrates a unified bow-tie analysis diagram for risk assessment of all identified risks (i.e. R_i= risk event i, $(i = 1, ..., 4)$; $F_{ij} = j_{th}$ risk factor of risk event i and L_{ij}=risk impact i of risk factor j, while $i = 1, ...4$ and $j = 1, ..., n$).

3.1. Method

With advancements in computer technology, decision support systems have become essential computer-based information systems that help decision-makers select a solution among the alternatives to a problem [41]–[46]. Analytic Hierarchy Process (AHP) is a widely used Multi-Criteria Decision Making (MCDM) method for mathematically transforming the judgments of decision makers'/experts' into numerical results in a robust way [47], [48]. AHP is similar to the methodology used in common-sense decision-making by providing many advantages in terms of its simplicity in handling multiple criteria [49]. It has been broadly used for MCDM problems by estimating weights through pairwise comparisons of criteria and decision elements to measure, rank, and evaluate the decision choices. During pairwise comparisons, AHP allows a degree of inconsistency that may occur. However, it cannot capture the uncertainty of preference ratings for the scoring criteria. Fuzzy AHP provides the opportunity to overcome this problem by allowing decision makers to evaluate their preferences within a reasonable interval in terms of the fuzzy scale instead of the AHP scale [48]–[50]. The fuzzy AHP is the extension of conventional AHP in order to be able to consider the fuzziness of the decision makers. It allows interaction with the system via multi-criteria structures at different levels by taking advantage of fuzzy logic to handle problems with uncertain and imprecise data [48], [51], [52]. The main steps of fuzzy AHP method are adopted as follows: Step 1:Classify the decision makers based on factors, i.e. age, education, experience, experience, profession position (Table 6 given in [23]). Step 2: Calculate weighting score of each expert. Step 3: Perform aggregation to obtain a joint fuzzy opinion that takes into account with the associated weight of each expert for each risk and consequence. Step 4: Obtain the final fuzzy probability score for each risk and consequence.

Fuzzy set theory is a theory where "vague" values are assigned to a set of real numbers. This technique represents uncertain degrees of truth as real numbers ranging from completely false, 0, to completely true, 1 [53]. Fuzzy logic theory is flexible and easily adaptable to different concepts, in which it is applied to different areas of research. It is very subjective because linguistic values are given a numerical representation and is an essential technique for dealing with uncertainties in research via fuzzy membership functions [54]. This technique converts qualitative assessments into statistical and numerical values for the ease of analysis. A fuzzy membership function is usually defined as:

$$f(x) = \begin{cases} 1 & \text{if } x \text{ is definitely a member of the set} \\ 0 & \text{if } x \text{ is definitely not a member of the set} \\ 0 < x < 1 & \text{if } x \text{ is a member of the set to a certain degree} \end{cases} \tag{1}$$

A fuzzy membership function has multiple states depending on the domain of the data set.

Fuzzy variable's states are representing the linguistic concepts of fuzzy sets: very low, low, medium, high, very high etc. A membership function for a fuzzy set "A" on the universe of discourse x is defined as $\mu_A : x \longrightarrow [0,1]$, where each element of x is mapped to a value between 0 and 1 [55]. In a triangular fuzzy membership function as in Figure 7, given in [23], a number is expressed as $A = (a_1, a_2, a_3)$ and the membership function is defined as:

$$\mu_A(x) = \begin{cases} 0 & x < a_1 \\ \frac{x-a_1}{a_2-a_1} & a_1 \le x \le a_2 \\ \frac{a_3-x}{a_3-a_2} & a_2 \le x \le a_3 \\ 0 & x > a_3 \end{cases} \tag{2}$$

In this study, the expert judgment method was used to collect opinions about each risk event based on their intellectual characteristics. Each expert had different attributes, such as age, experience, workplace position, and education level. To overcome the subjectivity of experts, expert weighting with fuzzy AHP was adopted, considering their attributes. Score ratings were assigned to each factor to calculate the expert weighting according to their attributes. Table 6, given in [23], shows the assigned score ratings for the experts' attributes [56], [57].

The three experts included in the study have the following attributes: the first expert is 25 years old with 3 years of experience as a cuisine worker with a bachelor's degree; the second expert is 35 years old with 13 years of experience as a restaurant manager with a PhD degree; and the third expert is 29 years old and has 6 years of experience as a restaurant manager with a master's degree. After assigning rating scores, the following relationship is used to calculate the weight of each expert [25]:

$$W_u = \frac{S_u}{\sum_{u=1}^{M} S_u} \tag{3}$$

where: W_u – weight of expert u, and S_u – total score of expert u, $u = 1, 2, 3$. The calculated expert weighting of each expert can be found in Table 7 given in [23]. Each risk has multiple risk factors that may cause its occurrence according to each expert's opinions. Therefore, the following relaitonship is used to perform an aggregation in order to analyze the effect of each basic risk event with the expert's opinions by using the aggregated fuzzy probability set (M_i) of each risk event as given in [26]:

$$M_1 = \sum_{i=1}^{m} w_j \bigotimes A_{ij} \tag{4}$$

where w_j is the weight of j_{th} expert $(j = 1, 2, 3)$ and A_{ij} is the fuzzy number set of the linguistic expression for i_{th} risk of j_{th} expert (see Table 3). Table 8 given in [23] shows the calculation of all aggregated fuzzy probability sets for each risk event with the corresponding risk factors. A sample calculation for the aggregated fuzzy probability set (M_1) of R_1 for F_{11} is

$$\begin{aligned} M_1(for\ F_{11}) &= 0.22 \bigotimes (0.1, 0.3, 0.5) + 0.44 \bigotimes (0.0, 0.1, 0.3) + 0.34 \bigotimes (0.1, 0.3, 0.5) \\ &= [(0.1 * 0.22 + 0.0 * 0.44 + 0.1 * 0.34), \\ &\quad (0.3 * 0.22 + 0.1 * 0.44 + 0.3 * 0.34), \\ &\quad (0.5 * 022 + 0.3 * 0.44 + 0.5 * 0.34)] = (0.056, 0.212, 0.412) \end{aligned} \tag{5}$$

On the other hand, the risk impact and risk impact likelihood are also calculated using (2) in order to analyze the consequences of risk factors. Table 9 given in [23] shows the calculation of all aggregated fuzzy impacts and likelihood for each risk factor. A sample calculation for the aggregated fuzzy probability set (M_1) for fuzzy impact set, and fuzzy impact likelihood set of

R_1 for L_{11} are given as (6) and (7), respectively:

$$\begin{aligned} M_1(for\ fuzzy\ impact) &= 0.22 \bigotimes (5,7,9) + 0.44 \bigotimes (5,7,9) + 0.34 \bigotimes (7,9,10) \\ &= [(5*0.22 + 5*0.44 + 7*0.34), (7*0.22 + 7*0.44 + 9*0.34), \\ &\quad (9*0.22 + 9*0.44 + 10*0.34)] = (5.68, 7.58, 9.34) \end{aligned} \tag{6}$$

$$\begin{aligned} &M_1(for\ fuzzy\ impact\ likelihood) \\ &\quad = 0.22 \bigotimes (0.5,0.7,0.9) + 0.44 \bigotimes (0.5,0.7,0.9) + 0.34 \bigotimes (0.5,0.7,0.9) \\ &\quad = [(5*0.22 + 5*0.44 + 7*0.34), (7*0.22 + 7*0.44 + 9*0.34), \\ &\qquad (0.9*0.22 + 0.9*0.44 + 0.9*0.34)] = (0.5, 0.7, 0.9) \end{aligned} \tag{7}$$

4. Data Analysis

The obtained values for the aggregated fuzzy probability, fuzzy impacts, and fuzzy impact likelihood of each risk factor, given in Tables 8 and 9 in Section 3, were then used to analyze the causes and consequences of these risk factors. For this purpose, bow-tie analysis is used to analyze the causes and consequences of each identified risk, R_i, on food delivery services for restaurants. As can be seen in the proposed framework given in Figure 4, FT and ET are considered to analyze the probability score of all the risk factors and impact score of all risk likelihood for each risk event. It is worth mentioning that FT contains all the risk factors that may affect the risk event, whereas ET contains risk likelihood and risk impact based on the corresponding risk factors. The FT analysis is combined with aggregated probability fuzzy numbers through "OR" gates to get the total probability score of the risk event, besides ET uses discrete analysis of likelihood and impact to get the total impact score. The analysis of FT and ET using the proposed framework is presented in the following sub-sections.

4.1. Fault tree (FT) analysis

Fault tree analysis was performed to determine the total probability score during the occurrence of a risk event. The total probability score, as given in equation (8), of the fault tree analysis can be calculated using the traditional approach [26]. However, it should be noted that, because of the unavailability of crisp data, it would be realistic to use (9) for fuzzy FT analysis instead of its traditional form. The total probability score of the fault tree for each risk event can be found in Table 10, given in [23]:

$$P_{(OR)} = 1 - \prod_{i=1}^{n}(1 - P_i) \tag{8}$$

$$\tilde{P}_{(OR)} = \tilde{1} \ominus \prod_{i=1}^{n}(\tilde{1} \ominus \tilde{P}_i) \quad where\ \tilde{1} = (1,1,1) \tag{9}$$

A sample calculation of the probability score for R1 can be given as follows:

$$\begin{aligned} &Probability\ score\ for\ R = \\ &\quad [1 - ((1-0.056)*(1-0.168)*(1-0.412)*(1-0.144) - (1-0.1))], \\ &\quad [1 - ((1-0.212)*(1-0.324)*(1-0.612)*(1-0.3) - (1-0.3))], \\ &\quad [1 - ((1-0.412)*(1-0.524)*(1-0.812)*(1-0.5) - (1-0.5))] \\ &\quad = (0.6442, 0.8987, 0.9868) \end{aligned} \tag{10}$$

4.2. Event tree (ET) analysis

The event tree analysis is carried out to determine the total impact score of each risk event. The following relationship is used to calculate the total impact score of the event tree of each risk event [13]:

$$\tilde{L}_k = \frac{\sum_{j=1}^{N} L_{ij}(\text{impact}) \otimes L_{ij}(\text{likelihood})}{\sum_{j=1}^{N} L_{ij}(\text{likelihood})} \tag{11}$$

where $\tilde{L}_k$ is the total impact score of a risk event k, and L_{ij} = risk impact i of risk factor j, while $i = 1, \ldots, 4$ and $j = 1, \ldots, n$. Table 11 given in [23] shows total impact score of each risk and a sample calculation for R_1 can be given as:

$$\begin{aligned}
R_1 = {} & \frac{[(5.68,7.68,9.34)\otimes(0.5,0.7,0.9)]+[(7,9,10)\otimes(0.144,0.344,0.544)]+[(5.44,7.44,9.22)\otimes(0.066,0.232,0.432)]}{(0.5,0.7,0.9)+(0.144,0.344,0.544)+(0.066,0.232,0.432)} \\
&= [(5.68, 7.68, 9.34) \otimes (0.5, 0.7, 0.9)] = (5.68 \times 0.5), (7.68 \times 0.7), \\
&\quad (9.34 \times 0.9) = (2.84, 5.38, 8.41) \\
&= \frac{(2.84, 5.38, 8.41) + (1.008, 3.096, 5.44) + (0.3590, 1.72608, 3.983)}{(0.71, 1.276, 1.876} \\
&= (\frac{4.207}{0.71}, \frac{10.198}{1.276}, \frac{17.829}{1.876}) = (5.9254, 7.9922, 9.5038)
\end{aligned} \tag{12}$$

4.3. Defuzzification

Probability and impact scores were calculated as fuzzy numbers. These numbers were defuzzified to obtain crisp numbers. The defuzzification of a fuzzy number is important as it can help rank the impact and likelihood of a risk event [39]. In the study, the most commonly used CoA (Center of Area) approach is adopted for defuzzification [58] as

$$X^* = \frac{\int v_1(x)xdx}{\int v_1(x)dx} = \frac{\int_{a_1}^{a_2} \frac{x-a_2}{a_2-a_1} xdx + \int_{a_2}^{a_3} \frac{a_3-x}{a_3-a_2} xdx}{\int_{a_1}^{a_2} \frac{x-a_2}{a_2-a_1} dx + \int_{a_2}^{a_3} \frac{a_3-x}{a_3-a_2} dx} \tag{13}$$

where X^* – defuzzified output, $v_i(x)$ – aggregated membership function, and x – output variable. The following relationship is engaged to triangular fuzzy numbers for defuzzification of triangular fuzzy numbers a_1, a_2, a_3:

$$X^* = \frac{1}{3}(a_1 + a_2 + a_3) \tag{14}$$

and Table 12 given in [23] shows defuzzified probability scores and impact scores for each risk.

4.4. Sensitivity analysis

Sensitivity analysis (SA) can be defined as a systemic approach of quantitative evaluation to identify the weakest links and important risk sources in the system. In this study, to determine how each risk event contributes to the proposed framework, SA was performed. The SA approach evaluates the sensitivity of an input event, whereas other input events remain constant [26, 39]. In this study, the defuzzified risk probability scores were re-evaluated using the SA approach, where one of the risk factors of the risk event is eliminated while other events remain constant. The aim was to show the level of significance or impact of risk factors on risk events. In addition, a sensitivity analysis has been proposed to identify the most important input events and measure the risk of the corresponding events. Table 13 shows the new probability risk scores when each risk factor for each risk event is eliminated. Eqn (8) was used to calculate the probability score after the SA approach was adopted. Hence, the calculated probability score of the risk event, that is, the probability score of R_1, was found to be 0.843.

Subsequently, by eliminating each risk factor (that is, F_ij, which belongs to its risk event, the new probability score is obtained, $\hat{R}_1$ $(i = 1, 2, 3, 4)$ are obtained respectively as shown in Table 13 given in [23]. The R_1 was calculated as 0.824 by eliminating the risk factor of F_{11} for $\hat{R}_1$. A lower probability score indicates a greater importance of the failure probability of the risk event. This means that the elimination of any risk factor that can lead to a higher probability score will reduce the risk likelihood more than in the case of other eliminations. The detailed discussions of the identified risks and consequences given in the article can also be found in [59]. It is worth mentioning that the adoption of risk prioritization process was applied as a new contribution in the context of this research by designing a Risk Priority Matrix (RPM). Risk prioritization is the process used to analyze risks and identify the order in which they are mitigated. Additionally, in this process, an RPM is designed for defining which risks have the highest priority to the business and need remediated first [60].

5. Findings and Discussion

This section presents and discusses the findings of the study, or more specifically, an assessment of risk management to eliminate potential risks that may occur in restaurant delivery services. The risks are categorized as supply, operational, demand, and macro risks with their corresponding risk factors. This study intended to examine the effects of these risks on a restaurant's supply chain using a fuzzy-based bow-tie analysis. The proposed framework shows how each risk behaves in the supply chain and its consequences for the restaurant delivery service. The risks were measured using bow-tie analysis and prioritized using the RPM. The risks are categorized as low, medium, and high in the risk priority matrix given in Table 14 in [23] based on [60]. As can be seen from the table, all the risks are in the category of either high or medium. Based on the aggregated responses of the experts (see Table 8 given in [23]), the results show that R_1 (supply risk) has a high probability score with a very high impact score, which can be prioritized as a high risk in the matrix. This proves that the identified five risk factors of R_1, namely supplier bankruptcy, poor communication on quantity of required raw materials, logistics and transportation problems, wrong quantity delivered, and poor quality of raw materials, have the highest effect on the restaurant delivery service (RDS), which could lead to delays in operations, low inventory in the restaurant, and return raw materials to the supplier. Moreover, R_3 (demand risk) and R_4 (macro risk) have very high and high probability scores, respectively, with a high impact score that can be prioritized as a high risk in the matrix. It is worth mentioning that three basic events for R3, that is, demand uncertainty, demand variability, and change in the order of customers, have a high-risk effect on the RDS, which could lead to excess or low inventory of raw materials and low service quality. Similarly, R_4 (macro risk) has four risk factors: natural disaster, political unrest, government regulation, and pandemic, which have a high-risk effect on the RDS that could lead to the shutdown of restaurants, disruption in the whole food delivery service, and disruption in transportation. In addition, R_2 (operational risk) has a medium probability score with a medium impact score that can be prioritized as a medium risk in the matrix. R_2 has four risk factors: lack of employee experience or training, poor inventory management system, service failure, and poor communication, which have a medium risk effect on the RDS that could lead to wrong customer order, customer leaving the restaurant, and poor reviews and brand image. In summary, all identified risks have a high to medium effect on the supply chain of food delivery services. Hence, it is necessary to avoid and/or eliminate risk factors of risk events to improve the risk management process in the supply chain of food delivery services. For this purpose, a sensitivity analysis was performed by eliminating risk factors, as shown in Table 13. The probability score of R_1 is 0.843, and it is observed that by eliminating the risk factor F_{13} (logistics and transportation problems between supplier and restaurant) reduces its probability score to 0.687. This shows that F_{13} had the highest deviation in the probability score among all the risk factors of R_1. However, R_2 has a probability score of 0.727, and eliminating F_{24} (poor communication in the cuisine system) will have the most significant effect on the probability score by reducing it to 0.55. Similarly, the probability scores for R_3 and R_4 were 0.782 and 0.958, respectively. R_3's probability score is reduced to 0.398 by eliminating risk factor F_{33} (change in the order of customers), which has the highest effect on demand risk. Moreover, to reduce the risk probability score most effectively, the risk factor F_{44} (effect of the pandemic) of R_4 must be eliminated, resulting in a probability score of 0.819. Figure 8, given in [23], illustrates the sensitivity analysis of each risk event by eliminating each risk factor. The probability of occurrence for all risk events and their probability score after the elimination of any of their corresponding risk factors are shown in Figures 8 (a) to 8 (d) given in [23]. Figure 8 (a), given in [23], shows that eliminating any identified risk factors ($F_{11}, F_{12}, F_{13}, F_{14}$, F_{15} of supply risk will help mitigate the occurrence of this risk. As shown in Figure 8 (a) given in [23], the elimination of the risk factor with the highest deviation, F_{13} (logistics and transportation problems between supplier and restaurant), highly mitigates the occurrence of supply risk. Additionally, the occurrence probability of operational risk can be reduced by eliminating any of the identified operational risk factors ($F_{21}, F_{22}, F_{23}, F_{24}$), as illustrated in Figure 8 (b) given in [23]. This will help mitigate operational risk, and the elimination of the risk factor, F_{22} (poor inventory management system), highly mitigates the occurrence of operational risk due to its highest deviation. Figure 8 (c), given in [23], illustrates the occurrence probability of demand risk before and after eliminating any of its identified risk factors (F_{31}, F_{32}, F_{33}). As shown in the figure, the highest mitigation of demand risk is observed by eliminating the risk factor with the highest deviation, F_{33} (change in the order of customer). Similarly, Figure 8 (d) given in [23] shows probability of occurrence of macro risk with and without eliminating any of its identified risk factors ($F_{41}, F_{42}, F_{43}, F_{44}$). It succeeded in mitigating macro risk by eliminating any of its identified risk factors. The highest mitigation is observed by eliminating the risk factor with the highest deviation, F_{44} (effect of the pandemic). In conclusion, the results prove that the proposed framework improves the risk management process in the supply chain of food delivery services in a restaurant by mitigating the identified risks with their corresponding risk factors. Fuzzy AHP and bow-tie analysis have been widely used across various industrial sectors, particularly for risk assessment in supply chain management. Food supply chains at restaurants generally require a simple but strict sequential supply chain. Preparing customers' orders accordingly is the main goal for satisfying customers' expectations, and restaurants have to anticipate and manage potential risks. The proposed fuzzy-based bow-tie framework will help all the involved parties to quantify and identify these potential risks. Accordingly, this study has also identified the "causes and consequences" of these risks posed to a food delivery service by handling linguistic uncertainties. These uncertainties arise owing to variations in experts' opinions, which cannot be coped with traditional risk assessment. Consequently, the proposed framework provides improved risk quantification and identification for all involved parties by eliminating such uncertainties. Additionally, the framework provides a risk-management process, and credible decisions on the mitigation of potential risks can be made. The findings of this study show that such decisions affect the occurrence of a risk event, and hence, an increase in customer satisfaction can contribute.

6. Conclusions

This study was conducted to develop a framework for assessing supply chain risks in restaurants. The restaurant supply chain used in this study consists of three main entities: suppliers, restaurant cuisine systems as service providers, and customers. Supply, demand, operational, and macro risks were extracted and analyzed as the main risks posed to the supply chain. Supply risks are disruptions related to the supplier of raw materials to the restaurant, and this risk directly affects both supply and restaurant cuisine system entities in the supply chain. On the other hand, operational risks occur because of the restaurant's service system, and they are associated with restaurant management, cuisine systems, and inventory management. This risk poses a direct threat to the supplier, restaurant cuisine system, and customer entities in the supply chain. Moreover, demand risks may arise from customers and are usually associated with the volatility and variability of their demands. These risks affect the cuisine system and customer entities in the supply chain. Macro risks are external environmental factors that affect the entire supply chain, such as government regulations, pandemics, natural disasters, and social unrest. This study provides a framework that combines qualitative and quantitative techniques for risk identification and assessment by considering all supply chain agents (suppliers, customers, manufacturers, etc.) and their corresponding risk factors. Additionally, a sensitivity analysis was conducted to determine how each risk event contributed to the proposed framework to improve risk management. The outcome of the study shows that eliminating the risk factors of an event with the highest deviation will result in an improvement in the risk management of food delivery services for restaurants. The study was conducted with a limited number of experts from different restaurants in the national dimension. The selection of experts who participated in the study was based on the judgment of the researcher. Future studies should be conducted internationally in different restaurants with more experts using similar variables. Moreover, the study may be extended with the incorporation of the type-2 fuzzy-based bow-tie approach to handle imprecision and uncertainty for improving risk assessment. In this study, the occurrence of risk events and their consequences on customer satisfaction were tested for the first time. Similar studies are required to strengthen the evidence obtained for further research. Another extension of this study is to consider both customers and their perspectives to deal with risk mitigation in restaurant supply chain management.

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