

Article

Identifying Key Factors of Reputational Risk in Finance Sector Using a Linguistic Fuzzy Modeling Approach

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Abstract: Management of reputational risk is crucial for financial institutions to establish a solid foundation for strategic decisions, gain customer trust, and enhance resilience against environmental adversities, as they largely operate on digital platforms. Since this becomes even more significant as online transactions and digital interactions amplify the visibility and potential impact of reputational issues in the context of electronic commerce, it is essential to thoroughly investigate environmental factors to achieve a comprehensive understanding of reputational risk. However, measuring and evaluating their influence on reputational risk is challenging due to their inherent connection to human perception. This study aims to explore the factors influencing reputational risk of financial organizations to mitigate potential reputational losses by addressing uncertainties associated with concepts such as vagueness. The employed methodology integrates the Decision-Making Trial and Evaluation Laboratory and Fuzzy Cognitive Map techniques using linguistic fuzzy terms. This approach focuses on both the direct effects of factors on reputational risk and the indirect effects arising from interdependencies between factors. Linguistic fuzzy variables enable us to consider the hesitation of the experts and the vagueness of human judgment. To validate the results, factors are also weighted using the fuzzy Stepwise Weight Assessment Ratio Analysis (SWARA) method. The most influential factors identified by both methods are market value, revenue, risk culture, shareholder value, firm performance, reputation awareness, and return on equity. Additionally, factors affecting other factors include firm performance, revenue, and growth opportunities.



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Keywords: financial institutions; reputational risk management; risk assessment; decision-making trial and evaluation laboratory (DEMATEL); fuzzy cognitive map (FCM)

1. Introduction

Reputational risk (RR) and its management are becoming increasingly important for companies, especially in the context of electronic commerce, as it plays a crucial role in determining the firm's value in a competitive environment [1–4]. The perception of all stakeholders addressed by the company determines its reputation, and effective management of this perception influences the social standing of the company. Regardless of time or place, the concept of “reputation” remains vital for both legal entities and individuals [5]. Institutions must protect their reputation, a core corporate value, or mitigate the risk of encountering unforeseen situations in their operations because it builds trust with stakeholders, supports financial stability, and helps attract and retain talent. A damaged reputation can lead to a loss of credibility, financial setbacks, regulatory scrutiny, and operational disruptions. Protecting their reputation helps institutions mitigate these risks and maintain long-term success. Therefore, identifying and managing RRs is essential to take necessary actions for risk management. By understanding this in the best way, it is possible to describe the relevant factor components and to take the necessary actions at the point of risk management. According to Heidinger and Gatzert [5], the importance of RR, which is related to other risks, is increasing.

RR is particularly significant for banks and other financial institutions involved in electronic commerce. These institutions rely on resources provided by their customers, partners, stakeholders, and employees to sustain their operations. Effective management of these resources enables banks to achieve a sustainable structure [5]. Stakeholders' perceptions of banks are shaped by the presence of robust risk management processes. In this context, RR becomes crucial, as banks depend on effective risk management to build trust with their stakeholders [6–8]. A strong reputation allows financial institutions to more easily attract and retain customers, thereby enhancing their reputational value.

Classifying the factors affecting RR in a specific order or structure is challenging. Various studies in the literature address RR. For instance, Kunitsyna et al. [9] model uncertainty as a probabilistic event and provide a methodology for estimating potential losses using risk implementation factors. These factors include financial soundness, customer satisfaction, legal compliance, business continuity, corporate management, personnel competence, risk management, crisis management, and transparency [10]. However, this list is not limited, and RR has many interrelated sources. The key is to enable effective and continuous RR management. Linguistic variable modeling holds significant potential for contributing to risk analysis. The data used in risk analyses vary by degree of abstraction (hard to soft), domain (linguistic coordination), and interaction effects. Complex problems are often resolved by implicit knowledge (by someone saying, “this is the way we do it here”, with no further discussion), but this approach does not fully utilize organizational knowledge resources. Decision support systems designed around computing with words and fuzzy logic algorithms can play a valuable role in these situations. This paper presents a unique perspective by applying unconventional uncertainty management methodologies to the practical issue of RR assessment. Using linguistic variables offers risk managers a flexible tool for interacting with domain experts, helping them express subjective assessments of the numerous factors in a risk analysis.

The aim of this study is to investigate the factors influencing RR of financial institutions within the electronic commerce landscape to reduce potential reputational losses. What is meant by the investigation is the attempt to determine the most important factors affecting RR by considering the uncertainty based on human perception. Determining these factors allows companies to manage them, maintain them at a healthy level, evaluate them strategically, and define sustainability indicators within their risk appetite. For these reasons, it is important to determine and list the related factors. In this way, the development of strategic management frameworks that contribute to enhancing the sustainability of financial institutions within the electronic commerce environment can be facilitated. Since the concept of reputation risk is based on human perceptions, it is difficult to measure and quantify, as well as to calculate the net value exposed to reputation risk. Therefore, this study proposes using analytical methods that also consider the uncertainty based on human perception. This study has a pioneering mission to fill gaps in the existing literature by examining the nuances of RR through a lens that integrates computing with words principles, addresses human-induced uncertainties, and highlights the unique dynamics of the financial sector. The investigation includes understanding the dependencies between factors, the intensity and direction of their relationships, and the weights of their effects on RR. In this way, it can be possible to build an efficient roadmap for future RR-related studies.

This paper is organized as follows. The literature review of the risk management studies is presented in Section 2. A general overview of RR factors is presented for the finance industry in Section 3. The factor list and the methods used for prioritization of the factors are explained in Section 4. The factors are investigated by using fuzzy linguistic expert assessments, and the findings are discussed in Section 5. Conclusions and future research directions are presented in Section 6.

2. Literature Review

The use of fuzzy methods in risk management has been well documented in recent years, with numerous studies addressing different types of risks across various industries.

Fuzzy techniques have proven effective in handling uncertainty and providing more flexible decision-making frameworks. Ayyildiz and Erdogan [11] addressed risk reduction strategies for offshore wind farms using a spherical fuzzy SWARA and VIKOR approach, offering a comprehensive risk mitigation framework. Similarly, Erfani and Tavakolan [12] evaluated wind energy project risks using a combination of fuzzy group decision making and Monte Carlo simulation. Their study presents an innovative risk evaluation model for investment projects in the renewable energy sector. In the context of blockchain technology, Karaşan et al. [13] evaluated risk factors that companies may encounter using a hesitant Z-fuzzy linguistic DEMATEL and FCM approach. This study focused on understanding the degrees of importance among various risk factors, providing valuable insights for companies adopting blockchain technology. Several studies have introduced fuzzy techniques into failure modes and effects analysis (FMEA) and risk priority assessments. For instance, Djenadic et al. [14] combined fuzzy FMEA, AHP, and TOPSIS methods to improve the accuracy of risk evaluations by calculating risk priority numbers in complex systems. Akram et al. [15] proposed an ELECTRE-I approach under the hesitant Pythagorean fuzzy environment to rank risks, contributing to general risk evaluation methodologies. Chen et al. [16] developed a risk evaluation framework for urban wastewater treatment public-private partnership projects using an improved fuzzy cognitive map and evidence-based reasoning. Their work highlights the adaptability of fuzzy methods in infrastructure project risk management. Similarly, Cheng et al. [17] used a q-Rung orthopair fuzzy VIKOR approach to assess enterprise risk management in small and medium-sized enterprises, with a focus on sustainability.

In financial risk management, fuzzy methods have also been applied. Akomea-Frimpong et al. [18] analyzed financial risk management strategies in public-private partnership projects in Ghana using fuzzy data analysis techniques. Yazdi et al. [19] employed Pythagorean fuzzy SWARA for credit rating assessments in Iranian banks. Additionally, Quynh [20] extended the fuzzy TOPSIS approach to evaluate banking performance, while Roghani et al. [21] used fuzzy AHP to assess the risk of structural failure in sewer pipes. Operational risks within the banking sector have also been explored using fuzzy methods. Ghorbani et al. [22] applied a Delphi-fuzzy method combined with TOPSIS for managing operational risks in banks. Ahmed et al. [23] introduced an adaptive neural network-based fuzzy inference system (ANFIS) to develop a comprehensive banking risk index, focusing on capital, liquidity, operational, and credit risks. Roy and Shaw [24,25] employed fuzzy-BWM and fuzzy-TOPSIS for credit rating evaluations and mobile banking application risk assessments, respectively. Lastly, Yang [26] proposed a financial risk assessment model based on Choquet expectation and fuzzy membership estimation, contributing to the growing body of work in financial risk evaluation.

When it comes to reputational risk, research is still emerging. Adeabah et al. [27] reviewed the themes and methods used in the reputational risk domain, noting that the use of fuzzy methods in this area remains limited. Rajagopal et al. [28] quantified reputational risk using a fuzzy cognitive map in the pharmaceutical supply chain, and Wang et al. [29] explored the causal relationships between corporate social responsibility, corporate reputation, and brand equity using fuzzy-set qualitative comparative analysis.

Despite the extensive use of fuzzy methods in risk management, there is a noticeable gap in the literature regarding the application of fuzzy techniques to reputational risk in the finance sector. This study aims to fill that gap by employing advanced fuzzy decision-making tools to assess and manage reputational risk, particularly in financial contexts where uncertainties and multi-dimensional factors are prevalent.

3. Reputational Risk in Finance

According to the definition published by the Basel Committee of Banking Supervision [30], RR is the risk associated with unfavorable perception by clients, counterparties, shareholders, investors, debt holders, market analysts, other key parties, or regulators that may have an adverse impact on a bank's capacity to maintain current or forge new

business relationships and continue to access funding sources. The Basel Committee of Banking Supervision officially unveiled the Basel III Accord [31] in 2010, and the Basel IV Accord [32] in 2017. Basel standards aim to strengthen the regulation, supervision and practices of financial institutions at the international level in order to increase financial stability and to establish a comparable framework among member countries. The standards in practice generally concern the methods for calculating financial risks or countable risks (credit risk, market risk, counterparty credit risk, capital requirement, etc.). However, no approach or method is recommended regarding standard measurement methods for RRs.

Regardless of the industries in which the organizations operate, RR can be defined in general terms using the same terminology. In general terms, RR is the loss that will occur due to the unsuccessful results of the actions taken by a company as a result of its activities, or if the legal authorities do not comply with the regulations, due to the decrease in the trust of the customer in the institution or the possibility of damaging the corporate reputation. Such situations may cause loss of income or capital. RR refers to the loss that may occur as a result of failures in the activities of an institution or non-compliance with current legal regulations, as a result of the loss of trust in that institution or damage to the reputation of the institution. This affects whether the organization creates new relationships or maintains old ones. This risk can lead to legal action by the organization, financial losses, or reduced customer numbers. RR applies to all organizations. While maintaining a solid reputation is important for any organization, financial institutions should be more sensitive in this regard. Today, it can be argued that protecting the reputation of a financial institution is one of the most important risks faced by boards of directors [33]. One of the factors affecting the acquisition process of the controlling shareholder in national or international mergers and acquisitions is the reputation structure and degree of the acquired company [34]. Along with the corporate governance process, the ethical corporate behavior structure can also affect the agreement price in merger and acquisition processes as a result of an increase or decrease in reputation [34].

After the 2008 Mortgage crisis, with the publication and implementation of the internationally valid Dodd-Frank Law [35], which expanded the regulations regarding banks and their customers, provided more supervision of banks, and enabled them to take measures before possible crises, banks were less risky, and this perception was increased with the awareness created by customers. The effects of this new regulation were analyzed in the study conducted by Swanepoel and Lotriet [36] and it was observed that this new regulation makes significant contributions to the reputation gain of companies. The crisis that started in a bank in the banking sector can spread to the whole system by creating a systematic effect. This situation results in the loss of confidence in banks and a significant deterioration in economic stability and public order. For this reason, financial networks in the banking sector are extremely important in order to protect the public's goodwill towards banks and thus the reputation of banks. The banking sector becomes more resilient to crises as financial safety nets become stronger [33]. Good corporate reputation management will enable the bank to establish a solid infrastructure for strategic decisions, especially during crisis periods, and will gain the trust of the customers in an intensely competitive environment. Banking is a profit-oriented business. However, it is an institution of trust as a public good. Within this paradox, the bank should provide balanced corporate reputation management [37]. In order to manage RR, management must systematically identify and document all risks. All significant risks should be clearly understood and continuously evaluated by managers [38].

Regarding the process of measuring the RR, it is important to convey what the concept of reputation means within the period, sector, or field when it is examined. It is essential to determine the factors affecting RR by expressing RR over the concept explained. When determining the factors that affect RR, it is important to lay the groundwork for all possible factors to participate in the evaluation process. It has been observed by Gatzert and Martin [39] that firm reputation and RR have an increasing importance in recent academic studies and by using the "text mining" method on the year-end annual reports shared

by the companies. In order for any risk to be measured, it must first be clearly defined and have a quantifiable structure. Listing the influencing factors or giving their definition clearly does not mean that a numerical result can be obtained but can be considered as the first step. Regan [40] states that RR is defined as risk, that is, other risks in the general literature, and mentions that risk management is quite difficult, because reputation is very difficult to measure and there is no numerical expression of reputation. Although a mysterious entity, researchers have attempted to observe the valuable “reputation” by calculating the difference between book value and market value, as it has been the subject of some studies [41]. According to Regan [40] and Tonello [42], RR should be considered in an integrated way in enterprise risk management, that is, its effects on reputation and potential financial results should be considered when modeling key risks (operational risk) [43].

In academic studies on RR given in Table 1, it is generally said that the relationship between RR and operational risk should be considered as two separate risks that must be distinguished from each other. Most of these studies were carried out especially on the companies traded in the stock exchange and the movement in the market/equity price was examined when the operational risks (losses, errors, news) and negative situations they experienced were heard [44]. It has been emphasized in recent years that the concept of RR is a subject that has been studied and needs to be developed, and that both quantitative and qualitative academic studies are needed. On the other hand, in addition to the research on financial sector (especially banks) companies, corporate governance features and competencies are included and the extent of their effects on possible RRs are examined. It is necessary to examine both quantitative and qualitative structures and values, where RR management cannot be handled unilaterally, and to develop them in line with theories. It is important to be able to specify pure RR [45]. RR has many interrelated sources. The important thing is to enable effective and sufficient RR management and to make this situation permanent. At this point, it is at the forefront to determine the factors affecting RR and to create processes that allow acting on its management. It is important to develop suggestions in parallel with cause-and-effect relationships by understanding both qualitative and quantitative relationships.

Reputational Risk Models and Study Directions

The management of any risk is a process that occurs over time and is shaped according to the structure of the companies. In this process, it is important to separate the risks and follow their definitions, because the management of each risk requires a different process. The measurement of the effects also differs according to the types of risks that the firm may be exposed to. The first and most important step of the risk management process is to clearly define the risk in question. It is important to be able to determine how to identify the risk, what may cause such situations, the analysis of the probability of realization of these threat situations and what the impact sizes may be, to determine the actions to be taken. It is important to manage the RR, to define the relevant factors and to have a good understanding of the environmental factor components. However, it is difficult to reveal the consequences of RR. RR, which has uncertain fundamental effects and is not easy to measure, is often overlooked, trivialized, or marginalized [46]. In the study conducted on European Union banks reported by Mukherjee et al. [41], it was stated that banks use many quantitative and qualitative methods to explain their RR strategies and that the risk is not standard in the sector.

To our knowledge, there are limited studies about the evaluation of RR in the literature. Lemke and Peterson [47] tried to understand the key drivers of reputation in supply chains without using a quantitative method and concluded that the reputation can be built and managed if and only if the nature of it is understood well. Zhu et al. [48] researched the drivers of reputation for financial organizations by using text mining and building a relationship map between the words and the subcategories of RR. There are a few studies integrating FST with RR-related investigations. Rajagopal et al. [28] investigated the

correlation between RR and input drivers for a pharmaceutical supply chain by using Fuzzy Cognitive Map (FCM). Kumar et al. [49] modeled the Online Reputation Management (ORM) by using an integrated fuzzy Delphi-DEMATEL method. These studies model the uncertainty in the basic form where the uncertainty is assumed to arise only due to loosely set boundaries of the definition of the concept under consideration (i.e., high risk, low risk etc.). However, the uncertainty can also be caused by other factors such as lack of expertise, indeterminacy about the assessment, expert hesitancy, etc. There is no study in the literature considering more complex uncertainties caused by human factors. Moreover, there is no study focusing specifically on the RR of specifically financial organizations by considering the uncertainty. RR is directly related to human perception but there is no study in the literature investigating RR using research methods integrating computing with words principles. Therefore, this study focused on the investigation of the critical factors influencing RR in the finance sector based on linguistic fuzzy modeling considering human perception-related uncertainties, mostly caused by high uncertainties arising from qualitative measures of RR and the consequent expert indeterminacy.

Table 1. Determined factor list.

Category	Factor	Reference Studies
Environmental	Region	[5]
	Institution Type	[2,5,50–54]
	Growth opportunities	[39,50,55,56]
	Perceptions of stakeholders	[1]
Financial	Size (Asset)	[5,8,33,49–51,53,55–57]
	Leverage	[5,8,39,44,50,52,54,55,57–59]
	Assets' opacity	[8,39,52,54–56,58]
	Earnings Volatility	[8,55,58]
	Stock Price Volatility	[8,50,52,58]
	Firm Performance	[39,60]
	Revenue	[61]
	Return on Asset (RoA)	[5–8,55,59,61]
	Shareholder Value	[6–8]
	Return on Equity (RoE)	[58]
	Capital Efficiency	[8,57]
	Cash Flow Volatility	[56,60]
	Capital Cost	[8]
	Frequency of Dividends	[8,57]
	Market Value	[1–4]
	Loan Commitments	[62]
Organizational	Reputation awareness	[5,40,63,64]
	Risk culture (CRO, Risk Committee awareness)	[5,8,50,55,58,60]
	Age/Year	[5]
	Industrial Diversification	[8,59]
	Institutional Ownership	[8,50,57–59]
	Social Responsibility Support	-
	Assessment of Big auditors (PwC, EY, KPMG, Deloitte, etc.)	[51,52]
	Assessment of Big rating agency (S&P, Fitch, Moody's, etc.)	[54]
	Number of Fraud Issues	[3,65]

4. Materials and Methods

Most of the engineering methods need quantitative data to yield useful results and require precise information to achieve favorable results. However, in social science studies, most of the input is not quantitative. Moreover, qualitative data usually contain uncertainty and are not precise. Since social sciences include a high level of vagueness, it is hard to formulate the social phenomena as mathematical models. These issues make traditional mathematical approaches useless and create a significant weakness in representing real-life problems. Zadeh [66] proposed fuzzy set theory (FST) to model real-life uncertainties. RR is also a concept including vagueness due to being a product of human perception. As an efficient way of modeling the uncertainty, FST has a high potential to formulate social phenomena. Zadeh [66] proposed FST to express the uncertainties of real-world problems mathematically, in which the vagueness is caused by the lack of clearly defined rules about the class membership. So, if it is hard to define or measure a phenomenon with agreed/objective expressions, FST is a good option to formulate it.

Ordinary fuzzy sets (FSs) use numerical values, but people think with words [67]. Linguistic fuzzy modeling (LFM), proposed by Zadeh as the basic building block of the computing with words concept, is a useful approach that allows thinking in words and transforming them into FSs with the help of a linguistic estimation. The quality of a fuzzy model is measured by the following metrics: (i) interpretability and (ii) accuracy. Interpretability indicates the model's ability to express system behavior in an understandable way, while accuracy represents closeness to the real system. In LFM, increasing interpretability is a priority [68]. In this way, experts can think and evaluate more freely with words in a way similar to real life. In addition, more reliable results can be obtained by preventing data loss and deviations that may occur during the process of experts adapting to the mechanism of the method or translating their linguistic thoughts into numbers.

Since RR is a phenomenon entirely related to people's feelings, it can be said that research in this field based on the computing with words concept will make significant contributions to the field. There is no study in the literature investigating RR using computing with words-integrated research methods. There are limited studies (referred to in Section 3) considering uncertainty in the basic form but no study considering more complex uncertainties caused by human factors such as lack of expertise, indeterminacy, hesitation, etc. Moreover, there is no study focusing on the RR of financial organizations by considering the uncertainty arising from the perceptuality and ambiguity of qualitative factors, even in the basic form. This study aims to fill these gaps. The following subsections present the details of the materials and the employed methodology.

4.1. Materials

In the literature, lots of factors are mentioned as influencing factors of RR. To obtain a comprehensive set of factors, a literature analysis has been carried out and the factor list presented in Table 1 has been determined.

4.2. Methods

The investigation of RR includes complicated uncertainties because the level of RR can be determined with human perception and the influence of the factors can be assessed by using subjective domain expertise. Working with multiple experts can be a good practice for reducing the subjectivity of the results, and hesitation in the expert assessments (i.e., lack of consensus due to differences of opinion among experts) is inevitably faced, since the finance sector includes a huge number of business domains. Thus, hesitation should be considered in uncertainty modeling to obtain reliable results. Moreover, the model should consider the ambiguity in human perception regarding factors and the vagueness of their influence on reputational risk.

In the literature, the uncertainty is generally modeled by using FST and its extensions depending on the decision environment causing the uncertainty, such as inconsistent or incomplete information cases. There are several FST extensions to model more complicated

uncertainty types. For example, it may be hard to decide the degree of uncertainty due to some environmental factors like lack of expertise. Atanassov [69] proposed Intuitionistic Fuzzy Sets (IFSs), which enable us to consider the indeterminacy about the degree of uncertainty to enable better modeling under incomplete information. Indeterminacy may be caused by hesitancy about the uncertainty in some cases. Hesitation can be faced in two ways: (i) lack of consensus due to differences of opinion among experts, (ii) the situation where the expert cannot choose between multiple fuzzy sets/linguistic terms since experts may be unsure about their assessments. Torra [70] suggested Hesitant Fuzzy Sets (HFSs), allowing us to consider assessments for the uncertainty of an event. HFSs enable us to model the hesitation of the experts while making assessments. Zadeh [71] proposed z-number as an alternative thinking approach combining probability theory with the fuzzy set theory. Z-numbers simulate the human approach to uncertainties in everyday life very well. Z-number consists of two components: (i) the restriction on the values of an uncertain variable and (ii) the reliability measure about the restriction. For example, when asked about the duration of the journey between work and home, the classical answer consists of two parts, like “approximately half an hour”, “usually”. This study uses z-numbers in decision-making processes so that experts can more freely express what is on their minds.

Multi-criteria decision-making (MCDM) techniques are generally used for studies requiring expert assessments. The literature was analyzed to find a suitable approach for investigation of the factors influencing RR by considering uncertainty. This analysis showed that the criteria weighting approaches seem suitable for this study, since they try to measure the severity of the effect of the criteria on the objective.

Deciding the criteria weights is a very complex and challenging process. The criteria weighting (CW) approaches can be classified as direct and indirect methods depending on the source of information [72]. While indirect (analysis of variance, etc.) methods use decision maker assessment, direct methods (scaling, rank-weight, etc.) use large sets of statistical information. A similar classification is carried out for modern CW approaches as follows: (i) objective and (ii) subjective [73]. Since objective weighting uses mathematical techniques, they determine weights without decision makers' input. However, as a big disadvantage, they require quantitative input to make calculations. On the other hand, subjective weighting can be used with both quantitative and qualitative criteria since they use decision makers' input [73]. They are also easy to use and straightforward [73]. For this study, it seems suitable to use subjective CW approaches. In the literature, the most popular subjective CW approaches are weighted sum [73], weighted product [73], Analytic Hierarchy Process (AHP) [73–75], SWARA [76,77], Weighted Aggregated Sum Product Assessment (WASPAS) [76] and DEMATEL [78] methods. Results of AHP may be biased, as it contains internal parameters that need to be tuned. SWARA, WASPAS and DEMATEL methods may allow us to obtain more robust results. SWARA gives more reliable results than WASPAS for the cases with the priorities identified earlier based on some conditions [76]. The procedure of DEMATEL is more complex than SWARA but it is more reliable than SWARA since it validates the relations by measuring them in a two-sided manner.

The studies investigating RR and similar problems considering uncertainty were also analyzed. Rajagopal et al. [28] use Fuzzy Cognitive Map (FCM) to investigate RR for a pharmaceutical supply chain. Kumar et al. [49] propose a model for ORM by using fuzzy Delphi-DEMATEL. The fuzzy integrated methods proposed by Rajagopal et al. [28] and Kumar et al. [49] consider uncertainty, but the multi-dimensional nature of the available uncertainty needs more sophisticated uncertainty modeling approaches. The MCDM methodology proposed by Karaşan et al. [32] combines FCM and DEMATEL approaches based on a more sophisticated fuzzy frame consisting of hesitant fuzzy sets and z-numbers. Since it considers intricate uncertainties having multiple subcomponents, it is a robust and comprehensive approach considering highly multi-dimensional uncertainties. This methodology was successfully applied to different scenarios including highly multi-dimensional

uncertainties such as assessment of the blockchain risk assessment [32], hydrogen energy storage systems [78], hydropower plant location selection [79].

In the scope of this study, the hesitant fuzzy z-DEMATEL and FCM approach proposed by Karaşan et al. [32] is used for the investigation of the factors influencing the RR. The method serves the following requirements for this study:

- Investigation of the dependencies between the factors;
- Investigation of the intensity and the direction of the relations between the factors;
- Investigation of the weights of the effects of the factors on RR;
- Consideration of the uncertainties caused by measuring the level of RR with human perception;
- Consideration of the uncertainties caused by assessment of the influence of factors on RR by using subjective domain expertise.

The employed DM methodology integrates DEMATEL and FCM techniques by using hesitant z-fuzzy linguistic term sets (LTSs). The Hesitant Fuzzy Sets (HFSs) are used for modeling the hesitation of the decision makers and z-Number is used for modeling the vagueness of the human sense. DEMATEL is used for exploring the relations of the risk factors and FCM is used for determining the weights of the factors [32].

The employed hesitant fuzzy z-DEMATEL and FCM methodology, in the form suggested by Karaşan et al. [32], merges the assessments of all experts with the ordered weighted averaging operator at the beginning (let us say pre-merging) and then runs the calculation steps. In this study, the method was modified and used because it was evaluated that this pre-merging approach could cause more data loss, have low reliability, and reduce the accuracy of the results, because the evaluation obtained by pre-merging operation is actually an evaluation that does not exist in reality. In this study, DEMATEL and FCM calculations were applied to each expert opinion independently (without any pre-modification), and in the last step, the numerical crisp values obtained were combined with the arithmetic mean and compared with the threshold value. Thus, it is thought that a smoother approach that causes less data loss is achieved.

The steps of the employed hesitant fuzzy z-DEMATEL and FCM methodology are represented in Figure 1. The algorithm consists of several steps, as follows:

- Get input: Begin with a predetermined list of factors provided in Table 1.
- Assign linguistic terms: Assign linguistic terms for trapezoidal fuzzy numbers representing preciseness and triangular fuzzy numbers for reliability. These fuzzy numbers will be used for DEMATEL and FCM.
- Collect expert assessments: Gather assessments from experts for each factor combination, represented by a combination of trapezoidal and triangular fuzzy numbers (Equation (1)).
- Calculate fuzzy numbers: For each expert assessment and each factor combination:
 - Calculate the trapezoidal fused fuzzy number ($\tilde{F}_{ij}$) using the reliability value ($\tilde{R}_{ij}$) as a weight (Equations (2) and (3)).
 - Convert the fused fuzzy number into a crisp value (x_{ij}^c) for further calculations (Equation (4)).
- Build the direct influence matrix: Construct the fuzzy direct influence matrix (X) using the crisp values derived in the previous step (Equation (5)).
- Normalize the direct influence matrix: Normalize the direct influence matrix to create a normalized fuzzy direct influence matrix (D) (Equation (6)).
- Build the total influence matrix: Compute the fuzzy total influence matrix (T) by multiplying the normalized matrix with the inverse of identity matrix minus direct influence matrix ($(I - D)^{-1}$) (Equation (7)).
- Calculate threshold: Determine threshold values by calculating the maximum, minimum, and average values of the total influence matrix, applying specific weightings (0.3 for max, 0.2 for min, and 0.5 for average).

- Confirm influence: Merge the fuzzy total influence matrices from all experts using arithmetic averaging. Compare the values in the fuzzy total influence matrix with the threshold values to confirm significant influences.
- Construct direction matrix: For each confirmed influence, determine its direction to build a direction matrix.
- Build initial relation vector: Collect initial evaluations from experts on confirmed influences and construct an initial relation vector.
- Iterate convergence function: Iterate the convergence function until the model stabilizes, ensuring that the influences are consistent with the expert assessments (Equation (8)).
- Aggregate results: Aggregate the results from all experts by arithmetic averaging.
- Rank: Rank the factors based on the aggregated results, reflecting their relative importance as assessed by the experts.
- Generate output: The final output is a ranked and weighted list of factors, indicating their significance based on the expert evaluations and the integrated fuzzy logic model.

Pseudo-code of the integrated hesitant fuzzy z-number based on the DEMATEL and FCM method is given in Algorithm 1:

Algorithm 1: Integrated Hesitant Fuzzy z-DEMATEL and FCM Algorithm

INPUT: Predetermined factor list given in Table 1.

BEGIN

Assign LTSs for trapezoidal preciseness ($\tilde{P}$) and triangular reliability ($\tilde{R}$) for DEMATEL and FCM

Collect expert assessments $\tilde{A} = [\tilde{a}_{ij}]$ by using LTSs for each factor combination ($i \in \{1, n\}, j \in \{1, n\}$) as shown in Equation (1):

FOR EACH Expert assessment

FOR EACH Factor combination of each expert assessment

BEGIN

Calculate trapezoidal fused fuzzy number ($\tilde{F}_{ij}$) by using Equations (2) and (3):

Convert fused fuzzy number to crisp value (x_{ij}^C) as in Equation (4):

where

$$l_{i\min}^F = \min(l_{i1}^F, l_{i2}^F, \dots, l_{in}^F), r_{i\min}^F = \min(r_{i1}^F, r_{i2}^F, \dots, r_{in}^F), r_{i\max}^F = \max(r_{i1}^F, r_{i2}^F, \dots, r_{in}^F),$$

$$l_{ij}^C = \frac{l_{ij}^F - l_{i\min}^F}{r_{i\max}^F - l_{i\min}^F}, m_{ij}^C = \frac{\frac{m_{ij}^F + m_{ij}^F}{2} - l_{i\min}^F}{r_{i\max}^F - l_{i\min}^F}, r_{ij}^F = \frac{r_{ij}^F - r_{i\min}^F}{r_{i\max}^F - l_{i\min}^F}, rs_{ij}^C = \frac{r_{ij}^F}{1 + r_{ij}^F - m_{ij}^C}, ls_{ij}^C = \frac{m_{ij}^C}{1 + m_{ij}^C - l_{ij}^C}$$

END

Build the fuzzy direct influence matrix (X) as in Equation (5):

Normalize the direct influence matrix to build the normalized fuzzy direct influence matrix (D) by using Equation (6):

Build the fuzzy total influence matrix (T) as given in Equation (7):

Calculate the maximum, minimum, and arithmetic average for the total influence matrix.

Specify the threshold value by multiplying the maximum value by 0.3, the minimum value by 0.2, and the average by 0.5.

END

Merge the fuzzy total influence matrices of experts by arithmetic averaging.

Compare values of the fuzzy total influence matrix with the threshold values

IF The value is greater than the threshold values

THEN

Confirm an influence between the values.

END

FOR EACH Expert assessment

FOR EACH Confirmed influence

BEGIN

Decide the directions of the influences to construct a direction matrix.

Build the initial relation vector (I^k) by collecting expert evaluations for the confirmed influences

Iterate the convergence function by using Equation (8) until models are converged:

Aggregate the converged results.

END

Merge the results of experts by arithmetic averaging.

END

Rank the factors.

END

OUTPUT: Ranked and weighted factors

A similar analysis is also carried out using the SWARA method to verify the consistency of the results obtained. The results found by the two methods are compared and analyzed in the following section. The SWARA algorithm in the literature has been modified by using the same fuzzy LTSs.

$$\tilde{A}_{ij} = (\tilde{P}_{ij}, \tilde{R}_{ij}) = \left((l_{ij}^P, ml_{ij}^P, mr_{ij}^P, r_{ij}^P), (l_{ij}^R, m_{ij}^R, r_{ij}^R) \right) \quad (1)$$

$$\underline{R}_{ij} = \sqrt{\frac{l_{ij}^R + m_{ij}^R + r_{ij}^R}{3}} \quad (2)$$

$$\tilde{F}_{ij} = (l_{ij}^F, ml_{ij}^F, mr_{ij}^F, r_{ij}^F) = \underline{R}_{ij} \times (l_{ij}^P, ml_{ij}^P, mr_{ij}^P, r_{ij}^P) \quad (3)$$

$$x_{ij}^C = \frac{ls_{ij}^C \times (1 - ls_{ij}^C) + rs_{ij}^C \times rs_{ij}^C}{1 - ls_{ij}^C + rs_{ij}^C} \quad (4)$$

$$X = [x_{ij}^C] \quad (5)$$

$$D = \min \left\{ \frac{1}{\max_i \sum_{j=1}^n \tilde{a}_{ij}}, \frac{1}{\max_j \sum_{i=1}^n \tilde{a}_{ij}} \right\} \times X \quad (6)$$

$$T = D \times (I - D)^{-1} \quad (7)$$

$$s_i^{(t+1)} = f \left(s_i^{(t)} + \sum_{j \neq i}^n s_j^{(t)} \times w_{ji}^{(\mu)(t)} \times w_{ji}^{(r)(t)} \right) \quad (8)$$

The steps of the employed SWARA methodology are represented in Figure 2. The algorithm consists of several steps, as follows:

- Get input: Start with a predetermined list of factors, as shown in Table 1.
- Arrange criteria: Organize the criteria based on the frequency of their indication by experts.
- Remove interrelated factors: Identify and remove factors that are interrelated to simplify the analysis.
- Determine unrelated factors: Create a list of factors that are unrelated and unique (denoted as $i \in I$).
- Sort factors by importance: Sort the remaining factors in descending order of importance.
- Determine importance differences: For each pair of successive factors, determine the difference in importance using a predefined set of linguistic terms.
- Calculate initial coefficient and weight values: Set the coefficient value $k_{(1)}$ and the weight $q_{(1)}$ of the first factor to 1 as a starting point.
- Calculate coefficients and weights: For each successive factor, calculate the coefficient $k_{(i)}$ and weight $q_{(i)}$ using expert evaluations of comparative importance (Equations (9)–(11)).
- Determine relative importance: Calculate the relative importance $v_{(i)}$ of each factor using the weights derived in the previous step (Equation (12)).
- Set threshold and final weights: Establish a threshold importance weight of 1%. Determine the final weights $w_{(i)}$ for each factor, adjusting them based on whether they exceed the threshold (Equation (13)).
- Aggregate weights: Combine the weights calculated for each decision maker to obtain an overall weighting for each factor.
- Rank: Rank the factors based on the aggregated weights to reflect their overall importance.
- Generate output: The final output is a ranked and weighted list of factors, highlighting their significance based on the SWARA algorithm and expert evaluations.

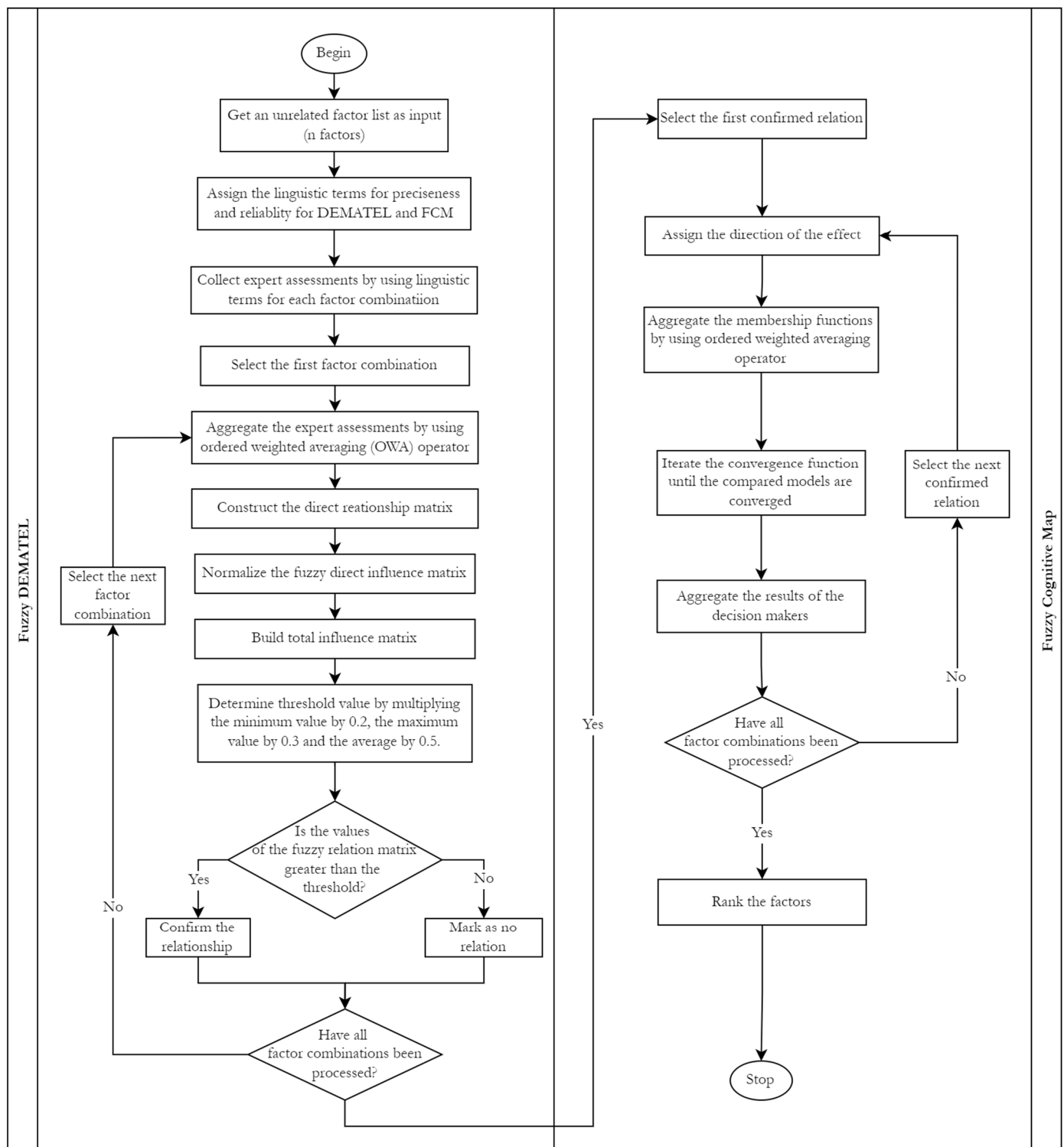


Figure 1. Illustration of the employed fuzzy DEMATEL + FCM method.

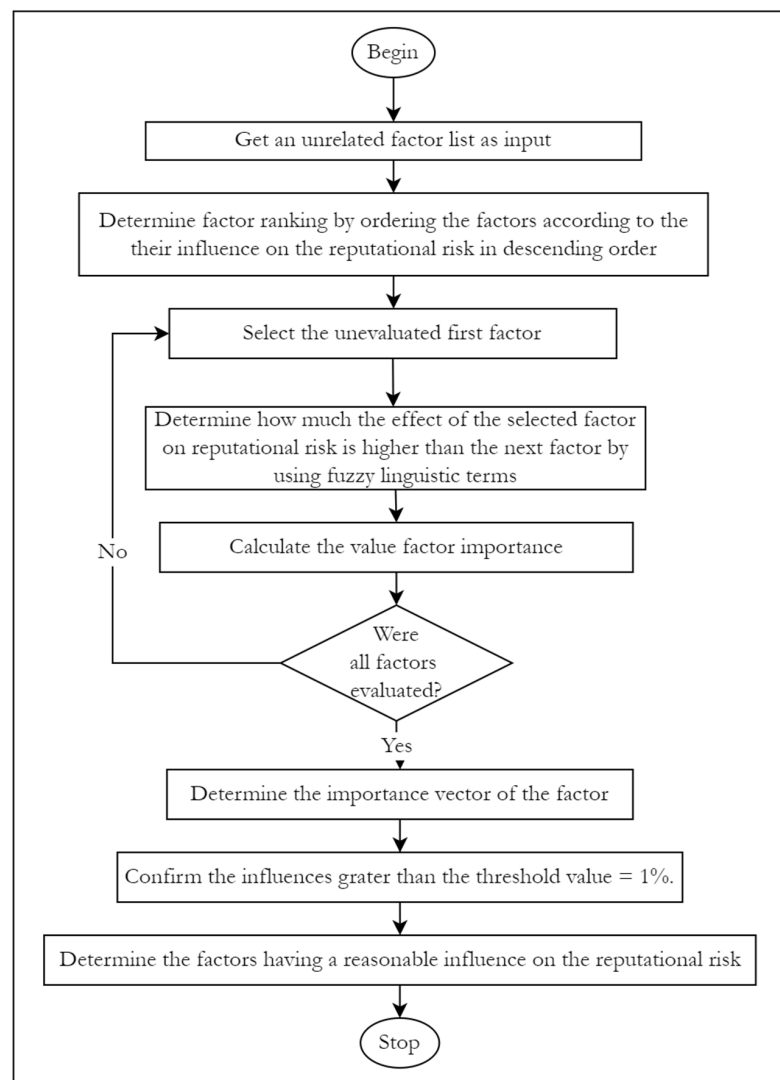


Figure 2. Illustration of the employed SWARA method.

Pseudo-code of the fuzzy SWARA method is as given in Algorithm 2:

Algorithm 2: Fuzzy SWARA Algorithm

INPUT: Predetermined factor list given in Table 1.

BEGIN

Arrange criteria according to frequency of indication

Remove interrelated factors

Determine unrelated factor list $(i \in I)$

Sort the factors according to importance in descending order: $i \rightarrow (i)$

Determine the importance difference between each successive factor pair by using the linguistic term set.

Set to 1 for the first coefficient value $(k_{(1)})$ and the first factor weight $(q_{(1)})$: $k_{(1)} = 1, q_{(1)} = 1$

Calculate coefficient values $(k_{(i)})$ and factor weights $(q_{(i)})$ of each succeeding criteria (i) with the help of the expert evaluations about the comparative importance of the factors $(s_{(i)})$ by using Equations (9)–(11):

Calculate the related importance of each factor $(v_{(i)})$ by using the relative assessments carried out in previous step by using Equation (12):

Set threshold importance weight as 1% and determine the final factor weights $(w_{(i)})$ as shown in Equation (13):

Aggregate the weights found for every decision maker

Rank the factors by using the aggregated results

END

OUTPUT: Ranked and weighted factors

$$s_{(i) \in \{2, \dots, n\}} = \frac{l_{(i-1)(i)} + m_{(i-1)(i)} + r_{(i-1)(i)}}{3} \quad (9)$$

$$k_{(i)} = s_{(i)} + 1 \quad (10)$$

$$q_{(i)} = 1/k_{(i)} \quad (11)$$

$$v_{(i)} = \frac{q_{(i)}}{\sum_{j=1}^n q_{(j)}}, \forall (i) \quad (12)$$

$$w_{(i)} = \frac{v_{(i)}}{\min(w_{(i)} > 1\%)} \quad (13)$$

5. Application

The presented methodologies were applied to the Türkiye environment. The application was organized by using the assessments of eight experts from Türkiye. Table 2 shows brief biographical information about the experts' experiences.

Table 2. Brief information about the experts.

Id	Experience (Year)	Institution	Title
1	21	Commercial Bank	Chief Risk Officer
2	18	Investment Bank	Chief Risk Officer
3	19	Commercial Bank	Risk Director
4	17	Participant Bank	Risk Director
5	15	Investment Bank	Risk Manager
6	13	Investment Bank	Risk Manager
7	11	Commercial Bank	Risk Manager
8	7	Participant Bank	Business Architect

5.1. Data

The factor list and the method presented in Section 4 were used in the application. The experts made individual assessments using the linguistic fuzzy term sets (LFTSs) proposed by Kaya et al. [79]. These term sets are given in Figure 3.

Table 3 shows example expert assessments made by using these LFTSs.

Table 3. Sample fuzzy linguistic expert assessments.

Step	Relation Magnitude	Reliability
DEMATEL	Between High Influence (HiI) and Low Influence (LoI)	High Determinant (HiD)
DEMATEL	Very Low Influence (VeLI)	Low Determinant (LoD)
DEMATEL	Between No Influence (NoI) and Low Influence (LoI)	Very High Determinant (VeHD)
FCM	Positive High (PH)	High Determinant (HiD)
FCM	Between Positive Absolutely High (PAH) and Positive High (PH)	Low Determinant (LoD)
FCM	Between Positive Very Low (PVL) and Positive Low (PL)	Very High Determinant (VeHD)

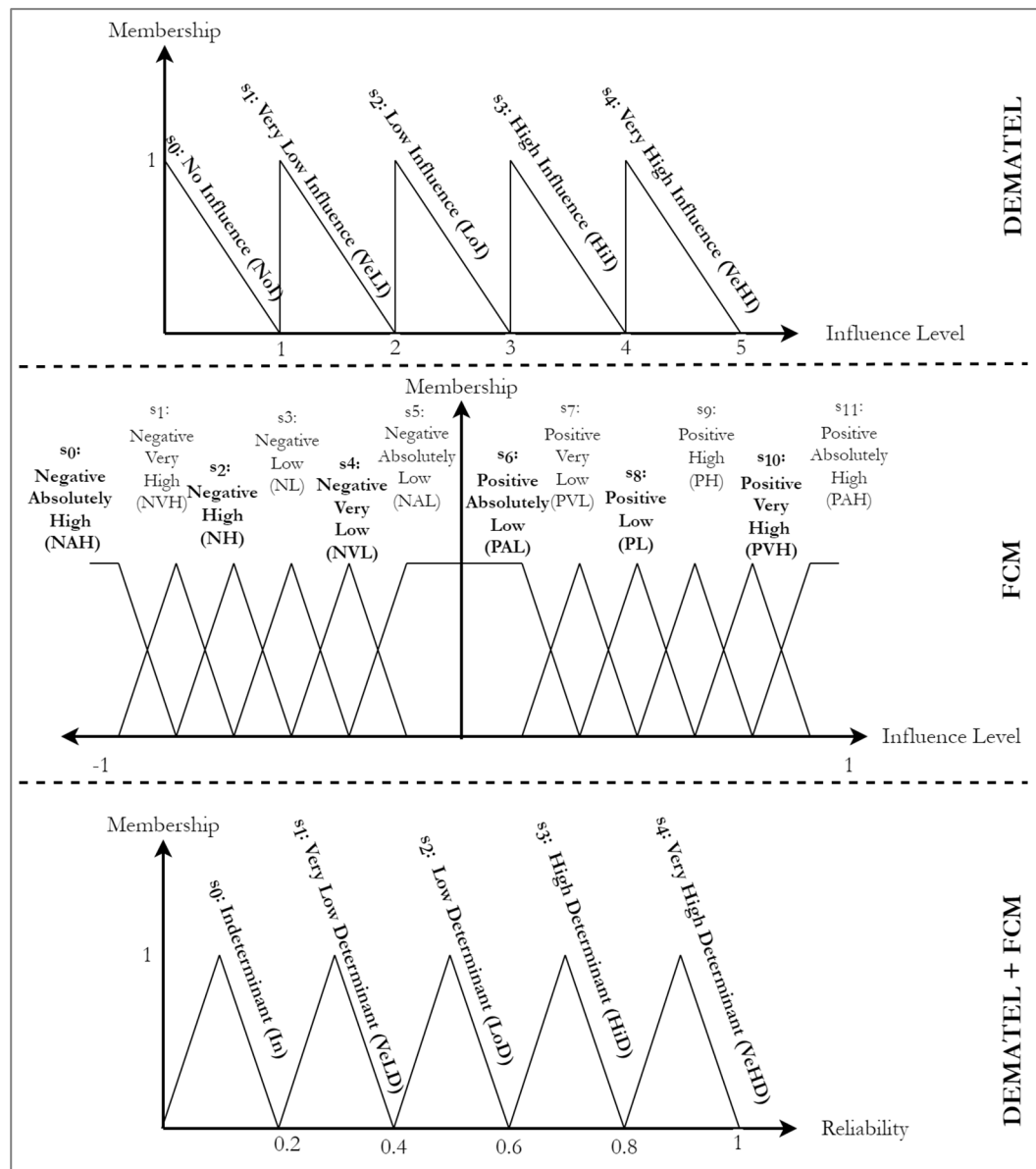


Figure 3. Employed linguistic fuzzy term sets.

5.2. Data Collection and Analysis Steps

Within the scope of this study, first, the most studied factors in the literature on RR were determined. The list was consolidated in line with expert opinions and reduced to 29 factors. Then, the data collection phase started.

In the first step, each expert was asked to make 29×29 DEMATEL evaluations. What is requested from experts here is to evaluate the relative effects of the factors on each other. In the table where data are entered, it is also requested that data be entered below the diagonal. Although this may seem like re-entering the same information in reverse at first glance, it is important for the method's own internal cross-checking and validation mechanism to work. Experts made these assessments independently of each other. In this way, the situation is avoided in which the consensus process may prevent some experts from expressing their opinions freely. Experts made their evaluations using fuzzy sets of linguistic terms. These term sets were determined by researching the most used linguistic term sets in the literature.

As a result of DEMATEL evaluations, validated influences were identified, and experts were asked to make linguistic FCM evaluations independently of each other for these

validated influences. Before the results of this step were shared with the experts, the experts were asked to make a third evaluation. By using the SWARA method integrated with a fuzzy linguistic term set, the factors are ranked from the most effective to the least effective in terms of their impact on the RR. Again, in this step, experts made independent evaluations.

5.3. Results and Discussions

In the scope of this study, algorithms were implemented in a spreadsheet application. Expert evaluations were also collected by a spreadsheet in linguistic form, then converted to fuzzy numbers. Table 3 shows example expert assessments made by using these LFTSs. The fuzzy evaluations were merged by using an arithmetic averaging operator. The merged evaluations are used as input for both algorithms for calculations. Since the fuzzy logic is a soft computing technique, the computation time is negligibly small. The fuzzy DEMATEL + FCM methodology contains an iterative subprocess managed by the convergence function given in Equation (8). In practice, this function converges between 5 and 10 iterations depending on the case. Thus, this subprocess can easily be managed in the spreadsheet application by repeating the process manually until it converges. After all these evaluations were collected, the remaining calculations were completed, and the obtained results are presented comparatively in Table 4.

According to the results obtained using the Fuzzy DEMATEL + FCM methodology, the factors most influencing RR in descending order are as follows: Firm Performance, Growth Opportunities, Loan Commitments, Capital Cost, Revenue, Risk Culture, Industrial Diversification, Shareholder Value, Cash Flow Volatility, Capital Efficiency, Market Value, Assets Opacity, Reputation Awareness, Institution Type, and RoE. The remaining factors show no meaningful effect on RR.

To verify these results, the SWARA methodology was also applied. Overall results are provided in Table 4 (colors are used to make it easier to recognize the same factor in both lists). According to SWARA, the factors with more than 1% influence on RR are as follows: Market Value, Size (Asset), Revenue, Risk Culture, Shareholder Value, Firm Performance, Reputation Awareness, RoA, Leverage, Perception of Stakeholders, and RoE.

The most influential factors that the two methods had in common are as follows: 1. Market Value, 2. Revenue, 3. Risk Culture, 4. Shareholder Value, 5. Firm Performance, 6. Reputation awareness, 7. RoE.

The fuzzy DEMATEL + FCM methodology further investigates the mutual interactions between factors. The factors having influence on the other factors in descending order were found to be as follows: 1. Firm Performance, 2. Revenue, 3. Growth Opportunities, 4. Capital Efficiency, 5. Risk Culture, 6. Perceptions of stakeholders, 7. Size (Asset), 8. Reputation Awareness, 9. RoE, 10. RoA, 11. Loan Commitments. The ranking based on the interaction/dependency of these identified factors with/on others is as follows: 1. Firm performance, 2. Revenue, 3. Risk Culture, 4. Reputation awareness, 5. RoE, 6. Market Value, 7. Shareholder Value. In particular, the first three of these factors have high interaction with each other. For these factors, the power of influencing the other factors is higher than the power of being influenced. For example, if the firm's performance changes, it causes a high change in many factors. On the other hand, changes in other factors cause a relatively small effect on the firm performance.

Both methodologies highlight meaningful influences on RR. Fuzzy DEMATEL + FCM identifies "Firm Performance, Revenue, Growth Opportunities, Capital Efficiency, Risk Culture" as key factors, while SWARA identifies "Market Value, Size, Revenue, Risk Culture, Shareholder Value". Healthy states of these factors positively impact the company's reputation, as they are critical indicators of financial development, investor interest, stability, and sustainability. This insight is particularly valuable for e-commerce companies, where market perception and stakeholder trust are crucial for sustained growth and competitive advantage.

Table 4. Results.

DEMATEL + FCM			SWARA			
Factor	Aggregated Membership	Rank	Factor	Weight	Normalized Weight	Rank
F7-Firm Performance	97.6%	1	F15-Market Value	73.9	31.8%	1
F8-Revenue	97.5%	2	F1-Size (Asset)	50.514	21.7%	2
E3-Growth opportunities	95.4%	3	F8-Revenue	20.955	9.0%	3
F11-Capital Efficiency	93.9%	4	O2-Risk culture (CRO, Risk Committee-awareness)	19.964	8.6%	4
O2-Risk culture (CRO, Risk Committee-awareness)	90.7%	5	F9-Shareholder Value	15.706	6.8%	5
E4-Perceptions of stakeholders	89.7%	6	F7-Firm Performance	12.193	5.2%	6
F1-Size (Asset)	88.9%	7	O1-Reputation awareness	10.651	4.6%	7
O1-Reputation awareness	88.7%	8	F3-Return on Asset (RoA)	9.110	3.9%	8
F10-ROE	87.2%	9	F2-Leverage	6.705	2.9%	9
F3-Return on Asset (RoA)	87.2%	10	E4-Perceptions of stakeholders	5.541	2.4%	10
F16-Loan Commitments	86.3%	11	F10-ROE	5.025	2.2%	11
O4-Industrial Diversification	83.1%	12	F11-Capital Efficiency	1.543	0.7%	12
F4-Assets' opacity	81.6%	13	F6-Stock Price Volatility	0.565	0.2%	13
F15-Market Value	80.2%	14	F16-Loan Commitments	0	0.0%	14
F9-Shareholder Value	75.9%	15	E3-Growth opportunities	0	0.0%	15
O8-Assessment of Big rating agency	75.6%	16	F4-Assets' opacity	0	0.0%	16
E2-Institution Type	73.7%	17	O4-Industrial Diversification	0	0.0%	17
E1-Region	70.6%	18	F12-Cash Flow Volatility	0	0.0%	18
O5-Institutional Ownership	63.7%	19	O7-Assessment of Big auditors	0	0.0%	19
O7-Assessment of Big auditors	62.0%	20	O8-Assessment of Big rating agency	0	0.0%	20
F2-Leverage	57.9%	21	F13-Capital Cost	0	0.0%	21
F14-Frequency of Dividends	57.1%	23	F5-Earnings Volatility	0	0.0%	22
O3-Age/Year	57.1%	23	O5-Institutional Ownership	0	0.0%	23
O6-Social Responsibility Support	57.1%	23	O9-Number of Fraud Issues	0	0.0%	24
O9-Number of Fraud Issues	54.8%	25	F14-Frequency of Dividends	0	0.0%	25
F6-Stock Price Volatility	40.5%	26	E1-Region	0	0.0%	26
F5-Earnings Volatility	34.1%	27	E2-Institution Type	0	0.0%	27
F12-Cash Flow Volatility	27.4%	28	O3-Age/Year	0	0.0%	28
F13-Capital Cost	20.5%	29	O6-Social Responsibility Support	0	0	29

Colors are used to make it easier to recognize the same factor in both lists.

Some factors identified by both methods have less impact on RR. Fuzzy DEMATEL + FCM identifies “Capital Cost, Cash Flow Volatility, Earnings Volatility, Stock Price Volatility, Number of Fraud Issues” as less impactful, while SWARA identifies “Region, Institute Type, Age, Social Responsibility, Frequency of Dividends”. These factors have minor impacts due to their indirect effect on the company’s financial indicators, investor interest, stability, and sustainability. For e-commerce platforms, managing factors like fraud issues and social responsibility can still play a significant role in maintaining consumer trust and brand reputation.

Differences are observed in both the list of factors affecting reputation and the list of factors that are said to be less effective by the employed methods. The results obtained with the Fuzzy DEMATEL + FCM method are more reliable because it is a more sophisticated method that allows for more flexible evaluation. This is because experts conducting the evaluation face fewer methodology-related constraints, can independently assess the bidirectional relationships between factors, and can reflect their indecisiveness in the evaluation process. For example, the assessment of the importance of factor 1 relative to factor 2 does not necessarily have to complement the assessment of the importance of factor 2 relative to factor 1. The methodology provides flexibility in this regard. Indeed, when the results are evaluated, it is seen that firm performance and revenue are more effective indicators in the creation of a company's reputational value than size or market value, which is quite reasonable based on human intuition. At the point where perception is extremely important in the creation of reputational value, while the positive development of performance and revenue has a positive effect, a negative situation in the development of these indicators leads to an increase in RR. The reliability of the Fuzzy DEMATEL + FCM method is not surprising because it is more sophisticated, advanced, and multidirectional. It also reflects the human hesitation to calculations. Thus, priority should be given to the improvement of these seven factors (1. Market Value, 2. Revenue, 3. Risk Culture, 4. Shareholder Value, 5. Firm Performance, 6. Reputation awareness, 7. RoE.) in studies aimed at reducing RR, especially for e-commerce businesses that operate in a highly dynamic and consumer-sensitive environment. It is observed that reputation risk management will directly affect company performance when addressed strategically, because the indicators determined as factors affecting reputation risk indicate the strengthening of the corporate and financial structure. If most of the effort is spent improving the first three factors, in practice, many factors that affect RR can be improved. Thus, it will be possible to manage resources better and obtain more effective results.

While this study provides valuable insights into the factors influencing RR for financial institutions, it is essential to consider how these findings might be impacted by real-world scenarios such as market fluctuations, market frictions, and significant economic events. These situations can have profound effects on a company's financial health and reputation, and thus on the applicability of the study's results. In real-world scenarios, market fluctuations, frictions, or major economic events, such as financial crises or recessions, can significantly alter the dynamics that this study explores. During such crises, companies may experience a sharp decline in revenue, deteriorating financial statements, and increased operational difficulties. This study's results, particularly the prioritization of factors like firm performance, revenue, and risk culture, may become even more critical as these elements are directly impacted by economic instability. However, the study assumes a relatively stable environment, which might not hold during severe economic disruptions. Companies that have not established robust risk management processes may find themselves more vulnerable to reputational damage during such periods, as their ability to respond effectively is compromised. Another assumption that may not fully hold in practice is the uniform impact of reputation management across different companies. While the study suggests that prioritizing certain factors can mitigate RR, the level of impact may vary depending on whether a company has already implemented preventive measures. Companies that proactively manage their reputation risk might experience less fluctuation in their reputational standing during crises. However, this does not guarantee a reputation boost; rather, it may prevent a significant decline. In this sense, the impact of reputation management is more about stabilization than enhancement, particularly in challenging economic environments. This study highlights factors that might not typically be considered significant by an ordinary businessperson, such as risk culture and reputation awareness. The study helps to underscore the importance of these elements, which are often overlooked in favor of more tangible metrics like revenue or market value. Risk culture, for example, plays a crucial role in how a company responds to and mitigates risk, affecting not only its immediate financial performance but also its long-term reputation.

The study thus contributes to a broader understanding of RR by emphasizing the need to consider these less obvious but equally important factors in strategic planning. It is worth considering whether companies that focus on reputational risk will indeed see a reputation boost when faced with significant economic challenges. The study suggests that attention to factors like firm performance, revenue, and risk culture is vital. However, in times of crisis, even well-managed companies may struggle to maintain their reputation. The key takeaway is that while reputational risk management can mitigate the extent of damage, it does not necessarily lead to a reputation boost during economic downturns. Instead, the primary benefit lies in damage control and the ability to recover more swiftly once conditions stabilize. While this study provides a solid framework for understanding and managing RR, it is important to acknowledge the potential limitations of its findings in real-world scenarios characterized by market instability and economic shocks. Companies must consider these factors when applying the study's insights, recognizing that the effectiveness of reputation management strategies may vary based on the specific economic context and the pre-existing risk management structures within the organization. In order to have a more comprehensive discussion, it would be appropriate to analyze operational risks as well. As a future study, a comprehensive decision process that holistically addresses the investigation findings obtained for different risk categories can be studied.

5.4. Limitations

Although the study was supported by a significant number of expert opinions and sophisticated decision-making methods, it has some limitations.

First, there is potential bias due to the study's reliance on expert opinions from Türkiye. The results may not reflect the general situation for all types and scales of banks worldwide, nor may they provide sufficient explanatory power for some non-banking financial institutions. For instance, the regulatory framework for the banking sector in Türkiye is well established, which naturally helps mitigate certain scenarios that could lead to financial risks. Consequently, experts' perceptions of risk are influenced by this situation. Therefore, the findings of this study may not adequately represent environments in countries or sectors where regulatory frameworks are not well established, as risk perceptions may vary. Additionally, Türkiye is a developing country that has also undergone a significant internet transformation. The results may represent countries with similar profiles, such as Greece, which are either developing or developed, quite well. In less developed countries, however, while the results are not entirely irrelevant, they may not be fully applicable. They only allow for some general conclusions under certain constraints. For all these reasons, it would be beneficial for global e-commerce businesses to expand the study to include diverse geographical insights to better understand international market dynamics and reputation management.

Second, the study reflects the risk perceptions of experts with specific experience, knowledge, and their risk perceptions. Although the sectoral experience of experts gives meaningful results due to their knowledge about the domain, it should not be ignored that there may be some difference between the risk perceptions of customers having different lifestyles, knowledge levels, etc., and those of experts. For this reason, the results obtained may not be comprehensive enough to include the opinions of all customers. On the other hand, since the effort to obtain such comprehensive information would go beyond the scope of one study, the solution that can be suggested here would be to support this study with new studies in the future. E-commerce companies, in particular, could benefit from integrating consumer feedback and social media sentiment analysis into RR assessments.

Third, the structure of the linguistic term sets adopted may also affect the results. Although hesitant fuzzy sets and z-number are used to minimize data loss in this direction, it is known that some parameters such as the cardinality of term sets have mathematical effects on the results. In this study, term sets commonly used in the literature were preferred to minimize data loss. Future research could explore customized linguistic term sets tailored to the e-commerce sector to enhance precision in RR evaluation. The employed fuzzy

DEMATEL + FCM method is a very complex and sophisticated method. Additionally, the research question of this study is relatively perceptually complex. For these reasons, it is extremely important that the method be well explained to experts in advance in terms of the reliability of the results. Otherwise, there may be a possibility of reaching erroneous conclusions due to misunderstanding of the research question. However, the method's internal cross-validation structure promises more unbiased results than SWARA and other similar decision-making approaches because, while in SWARA and similar methods, the expert must make the ranking, the fuzzy DEMATEL + FCM method creates a ranking by interpreting the independent evaluations together. This allows us to obtain more reliable results in social science subjects where hesitation may be high. This methodological rigor is particularly useful for e-commerce businesses, where rapid changes in consumer behavior and market conditions demand robust risk management frameworks.

Another limitation of the study is related to the threshold value used in DEMATEL. In this study, this value was determined as 0.2, and relationships exceeding this level were labeled as validated influence. This value of 0.2 was determined according to general acceptance based on other applications in the literature. Different threshold values may cause slight differences in results.

Lastly, there is a limitation related to the combination of expert opinions. Different approaches such as arithmetic average, weighted average, and data envelopment can be adopted. The arithmetic mean approach was used in this study. If it is desired for experts' experiences to affect the evaluation weights, it may be preferable to use a weighted average. However, it should be noted that when the number of experts is increased (eight experts is a high number compared to similar studies in the literature), the weighted average and arithmetic average will yield similar results. For e-commerce applications, considering the expertise level of different stakeholders (e.g., digital marketers, cybersecurity experts) could provide a more nuanced understanding of RRs.

SWARA also has important limitations. When the experts determine the difference in importance between two factors using linguistic terms, the results are directly affected by the size of the linguistic term set used. If the number of terms in the set is small (after the first few factors), the weights of the factors quickly converge to zero. Since this may cause the obtained weight values to be interpreted subjectively, the reliability of the method will decrease. To solve this, if the number of fuzzy linguistic terms is increased greatly, the terms begin to become meaningless as interpretability decreases, which means a decrease in reliability. If the weights are ignored and only the order is taken into consideration, the method will become redundant because experts are required to rank the factors in the first place. This ranking is made without the support of any analytical framework or mechanism. These mentioned problems are not specific to SWARA. Similar criticisms can be made for many different criterion weighting approaches such as FUCOM. In this context, SWARA does not have any significant disadvantages compared to other similar methods. Adopting a balanced approach in linguistic term sets could improve the robustness of risk assessments.

6. Conclusions

Risk management is the process of identification, evaluation, and control of the risks that may arise during the achievement of a certain goal of a business or a project. This process helps businesses achieve their objectives, use resources effectively, and reduce the risk of failure. Risks, significant for businesses, can hinder goal attainment and negatively impact various resources (such as time, money, and human resources). Therefore, a systematic strategy for risk management is essential. Accurate definition is essential for the successful management of any risk, including RR, which is challenging to measure numerically.

RR is particularly significant for financial institutions involved in electronic commerce, where the digital environment amplifies the visibility and potential impact of reputational issues. RR is included in the class of risks that are difficult to measure numerically. It is important to thoroughly research and understand the environmental components influenc-

ing RR in order to gain a thorough grasp of the RR, as these factors often relate to human perception, making them difficult to quantify. In other words, it is difficult to quantify and assess how they affect RR since the majority of them have to do with how people see things. Both qualitative and quantitative modeling can aid in measuring RR, but a clear and precise measurement approach is necessary.

In this study, eight experts from Türkiye assessed RR factors. They identified significant factors from existing literature and narrowed them down to 29 based on expert input. Using fuzzy sets of linguistic terms to prevent bias, experts evaluated the relative impacts of these factors independently. They then assessed the internal dependencies of the factors to confirm influences. The results were analyzed and presented for comparison, revealing that the most relevant factors for measuring RR are as follows: 1. Firm performance, 2. Revenue, 3. Risk culture, 4. Reputation awareness, 5. Return on equity, 6. Market value, and 7. Shareholder value. Positive development in these factors enhances reputational value, while negative developments increase RR.

The hesitant fuzzy z-DEMATEL and FCM approach provides a sophisticated framework for addressing multidimensional uncertainties in RR management. Traditional quantitative models, while powerful in handling large datasets, may struggle to incorporate this kind of subjectivity. Moreover, machine learning models require extensive historical data, which are often limited in the context of RR due to its qualitative nature. When compared with other methodologies, such as traditional statistical approaches or machine learning-based models for risk assessment, the use of fuzzy linguistic modeling in this study offers unique advantages and challenges. The employed approach is particularly robust due to its ability to model both the hesitations of decision makers and the uncertainty of human perceptions, which are necessary to accurately assess RR. Compared to traditional fuzzy approaches such as Fuzzy TOPSIS or Fuzzy AHP, it offers greater flexibility in capturing bidirectional dependencies and relationships between factors, without data loss from trying to fit experts' opinions to the method. It provides a detailed understanding of how factors such as company performance, revenue, and risk culture interact and affect RR. Thus, it models the inherent uncertainties and multidimensional risks associated with these perceptions more effectively than traditional fuzzy decision-making techniques, which may not fully account for the complexity of human judgment. The method's ability to reflect human hesitations makes it more reliable in capturing complex interactions that simpler fuzzy methods may miss. This results in a more comprehensive and accurate understanding of RR, which is vital for businesses looking to manage reputational risks in a volatile market. However, the z-DEMATEL and FCM approaches also present challenges. While relying on expert input allows for greater flexibility and adaptability, the method's effectiveness decreases when there is significant instability between different expert decisions, making the results highly sensitive to its parameters. In contrast, simpler methods such as Fuzzy AHP or Fuzzy SWARA are easier to implement and require fewer computational steps but may not capture the same level of interaction and uncertainty among factors. Therefore, they may be more useful for simpler problems. Despite being more computationally intensive, the z-DEMATEL and FCM methods offer a more accurate and refined analysis, especially for assessing multidimensional uncertainties in sectors where human perception significantly affects risk.

In conclusion, this study highlights the importance of performance, financial indicators, and risk management in managing the RR of financial institutions, especially within the electronic. This study provides a foundation for further research and practical applications, aiming to enhance the understanding and management of RR through innovative approaches like linguistic fuzzy modeling. The findings emphasize the need for ongoing research and development in this area to support the sustainable growth and resilience of financial institutions in the digital age.

As a future study, a risk management framework can be established to manage factors minimizing RR correctly since the governance of a properly defined risk will be clear and accurate. With the listing of the factors affecting the RR, the next step may be to make it

easier to measure numerically. Numerical models and methods can be developed with the formation of a sufficient number of observations and data on the factors determined in the governance of the relevant risk. In addition to all these, a more comprehensive analysis of the factors affecting RR can be carried out by compiling and analyzing publicly available data through methods such as web mining, in order to reflect the perceptions of different customer profiles.

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