



A Two-Stage Interval Type-2 Fuzzy Approach for Contract Renewal Risk Assessment in Non-Life Insurance Using BWM and Pareto Analysis



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Abstract: The accurate assessment of contract renewal risk at the individual policyholder level represents a critical component of risk management in non-life insurance and is essential for ensuring long-term business sustainability. In this study, a two-stage interval type-2 fuzzy decision-making framework was proposed to evaluate and classify policyholder renewal risk. The approach began with the identification of key risk factors (RFs) that exert the most significant influence on renewal outcomes and overall business risk. The relative importance of these RFs was expressed through predefined linguistic terms, which were systematically mapped to interval type-2 triangular fuzzy numbers (IT2TFNs). The Fuzzy Best-Worst Method (FBWM) was applied to derive the optimal weight vector of RFs. Subsequently, the values of the identified RFs were quantified based on available operational and historical insurance data. Using type-2 fuzzy algebra, a weighted normalized decision matrix was constructed. In the second stage, a novel Pareto analysis extended with interval type-2 fuzzy numbers (IT2TFNs) was introduced to classify policyholders according to their associated renewal risk levels. This integration enabled the simultaneous consideration of both factor weights and their fuzzy performance values, ensuring that high-risk policyholders are effectively distinguished from lower-risk groups. The proposed framework was validated through a real-world case study in the non-life insurance sector. By integrating the strengths of FBWM and fuzzy Pareto analysis, the framework provides an original and rigorous methodology for risk assessment in non-life insurance, contributing to both academic research and practical applications in the domain of sustainable insurance management.

Keywords: Insurance; Risk factors; Fuzzy Best-Worst Method; Fuzzy algebra rules; Pareto

1 Introduction

Insurance companies are institutional investors within the financial system of every country. Insurance can be defined as the provision of legal and economic protection against specific risks that threaten property and individuals [1]. Namely, by signing a contract (policy) between the insurer and the policyholder, the insurer assumes the policyholder’s risk in exchange for a premium paid by the policyholder. From the insurer’s perspective, the insurance contract implies that the insurer will bear the consequences of the risk materialization, i.e., compensate the policyholder for the resulting damage. One of the key issues in every insurance company is the analysis of the business risk level caused by the renewal of contracts with policyholders. Risk represents the probability of negative effects on the business and financial results and the position of the insurance company, while risk management is defined as the process of identifying, measuring, assessing, and controlling that risk [2].

In practice, risk management in insurance companies falls under the responsibilities of actuaries and underwriters. Actuarial science includes the identification, definition, and formulation of all necessary activities aimed at covering future financial obligations arising from concluded insurance contracts, through the application of actuarial techniques, methods, or models [3]. Actuaries define and propose to manage a risk measurement model for premium sufficiency and claims reserves, as well as their interdependencies in determining solvency. By measuring individual risks, it is possible to monitor their impact on the insurer’s financial strength, which in turn determines the position of the

insurance company. There are various criteria for classifying the risk of contract renewal with insurance clients. The most important and comprehensive classification criterion is based on the type of insurance: (a) life insurance and (b) non-life insurance. One of the most significant types of non-life insurance is property insurance. The importance of property insurance lies in its role in mitigating and overcoming the consequences of catastrophic damages, the financial consequences of which often exceed the capacity of insurance companies. Moreover, property insurance is important both at the individual level and at the level of the national economy.

This study considers non-life insurance that covers damage to material assets. Many practitioners also refer to non-life insurance as risk insurance, since it is possible to predict the occurrence of harmful events and their financial consequences. The amount of compensation paid to policyholders in non-life insurance is not predetermined and its financial effect is difficult to estimate. The duration of non-life insurance contracts is typically one year. During this period, multiple claims may arise. Upon contract expiry, policyholders are not obligated to renew the contract with the same insurer. Therefore, insurance companies must closely monitor market trends and, when necessary, undertake various activities aimed at retaining clients. In doing so, insurance companies may jeopardize their solvency and market position. Thus, the identification and measurement of actuarial risks represents one of the most important management issues within an insurance company.

The relative importance of RFs can be more accurately and precisely described using natural language rather than exact numerical values. The development of type-2 fuzzy sets theory [4] has enabled the quantitative representation of linguistic variables in an adequate manner. However, the use of type-2 fuzzy sets requires complex and extensive computational operations, and therefore, it has not been widely applied to real-world applications. IT2FNs, which represent a special case of type-2 fuzzy sets, are easier to use due to their reduced computational effort compared to general type-2 fuzzy sets. In the literature, a large number of studies can be found in which various uncertainties and imprecisions are modeled using IT2FNs. Many authors have suggested using IT2FNs [5–7], which capture the vagueness of natural language effectively, while requiring significantly less computational effort than general type-2 fuzzy numbers with different membership function shapes. In practice, it is commonly assumed that all RFs have equal importance. However, such an assumption is not sufficiently accurate, and it can be considered that a risk matrix based on this assumption contains certain errors, which can significantly affect the decision regarding the renewal of non-life insurance contracts.

In this study, a two-stage fuzzy model was proposed for assessing the risk of contract renewal with non-life insurance clients. In the first stage, the weights of RFs were determined by applying FBWM. In the second stage, client classification with respect to all RFs and their weights was conducted using fuzzy Pareto analysis.

Numerous subjective Multi-Attribute Decision-Making (MADM) approaches extended with fuzzy sets can be found in the literature, which have been used to determine the weight vector in an exact manner [8–10]. However, only a few studies have addressed the problem of risk assessment in insurance companies where the weights of RFs were determined precisely. In some studies [11–13], the determination of the relative importance of RFs is formulated as a fuzzy group decision-making problem. A fuzzy pairwise comparison matrix was established at the level of each Decision-Maker (DM), with elements represented by triangular fuzzy numbers (TFNs). Kefer et al. [12] performed aggregation of evaluations provided by DMs into a unified assessment using a fuzzy weighted ordered aggregation operator. The weight vector was then calculated using extent analysis [14], resulting in crisp values. Lukić et al. [13] constructed a fuzzy pairwise comparison matrix for each DM, and the weight vector was derived using the Fuzzy Analytic Hierarchy Process (FAHP), with elements described by TFNs. The aggregated weights were calculated using a fuzzy geometric mean. Although the Analytic Hierarchy Process (AHP) is widely used in the literature and well understood by researchers, it is often difficult for practitioners to interpret.

Banduka et al. [11] assessed the identified failures according to four RFs of unequal importance. The relative importance of RFs was expressed through a fuzzy pairwise comparison matrix whose values were modeled by IT2FNs. The weight vector was calculated using a fuzzy geometric mean. Therefore, the resulting weights were also described by IT2FNs. In real-world organizational systems, such as insurance companies, DMs can more easily evaluate the relative importance of RFs by comparing the most and least important ones, as in the Best-Worst Method (BWM) [15]. BWM is based on forming two pairwise comparison matrices. It is assumed that the best and worst criteria are first identified by DMs. All criteria are then compared with respect to the best and worst ones. A nonlinear optimization model is used to determine the weight vector. After obtaining the final results, the consistency level of the comparisons should be calculated. The consistency is defined according to the study by Rezaei [15].

Several studies have proposed the modifications of BWM with type-2 fuzzy numbers [16–19]. Wu et al. [16] suggested that the relative importance of criteria could be described using predefined linguistic expressions modeled by the interval type-2 trapezoidal fuzzy numbers (IT2TrFNs). The objective function was defined as the minimization of the maximum absolute gaps. The optimal solution was obtained from the intersection of linear constraints—one for the weights' sum and another for IT2TrFNs. Defuzzification of the weights' sum was conducted using the center of area method [20]. Criteria weights for supplier selection were determined [17]. Aleksić et al. [18] modeled the relative importance of RFs using IT2FNs, allowing significantly reduced computational time compared to IT2TrFNs. Since

the assessment of RF importance is framed as a fuzzy group decision-making task, these authors have aggregated the opinions of DMs into a unique evaluation using a fuzzy geometric mean. The fuzzy nonlinear optimization model was formulated by analogy with the study by Wu et al. [16], and defuzzification of the weights' sum was performed using the iterative algorithm [21]. The consistency ratio (CR) was computed using the same process described by Rezaei [15] and Wu et al. [16] at the level of each DM.

One of the most widely used methods for classifying many items across different application areas is Pareto analysis. In this method, all items are classified into three categories according to a classification criterion. Class A includes items of the highest importance to the problem under consideration. It is commonly assumed that 5–10% of the total items belong to this category. The next 15% of items fall into Class B, which represents items of moderate importance, and DMs do not necessarily need to pay close attention to them. Class C contains the items of least importance for DMs in the given decision-making problem. Several studies can be found in the literature where the classification of items was performed with respect to multiple criteria [11, 12]. The values of these criteria were expressed using TFNs, and the classification criterion was defined as the product of the two. The classification of items was carried out using representative scalar values according to the rules of the conventional Activity Based Classification (ABC) method.

Chu et al. [22] assumed that the values of criteria could be either nominal or non-nominal. Classification was based on fuzzy rules in combination with conventional ABC method rules. Kefer et al. [12] addressed the problem of classifying suppliers in the building and civil engineering industry based on multiple criteria. The weighted normalized fuzzy decision matrix was constructed using fuzzy algebra rules. The classification criterion was defined as the Euclidean distance of elements in the matrix from the maximum or minimum value, respectively. The distances were sorted in descending and ascending order, respectively. Suppliers corresponding to the top 10% and bottom 80% of distances were assigned to Class A and Class C, respectively, while all others were placed in Class B. Banduka et al. [11] considered the classification of non-obligatory failures that may occur in automotive industry products. The values of these failures were taken from the Failure Mode and Effects Analysis (FMEA) reports. The elements of the weighted fuzzy decision matrix were constructed using fuzzy algebra rules [4]. The classification criterion was computed as the sum of the weighted criterion values, while representative scalar values were obtained using the defuzzification procedure [20]. In this way, the classification of non-obligatory failures was performed by applying the conventional Pareto analysis.

The motivation for applying this methodology stems from the fact that very few studies in the literature have addressed risk assessment in insurance companies using exact models. The broader objective of this research can be interpreted as the integration of Pareto analysis and BWM with IT2TFNs, i.e., the interval type-2 Fuzzy Best-Worst Method (IT2FBWM). This integration includes (a) the assessment of the relative importance of RFs using predefined linguistic expressions modeled by IT2TFNs, (b) the determination of a fuzzy weight vector of RFs using IT2FBWM, (c) a modified fuzzy Pareto analysis for determining the risk of contract renewal at the individual client level. This study is structured below. Section 2 describes the proposed fuzzy classification method. Section 3 illustrates the proposed algorithm through a real-life example. Sections 4 and 5 discuss and conclude this study, respectively.

2 Methodology

The fuzzy model that combines BWM with type-2 fuzzy sets for determining the weights of evaluation criteria and a modified fuzzy Pareto analysis for assessing business risk at the level of each insurance client is presented in Figure 1.

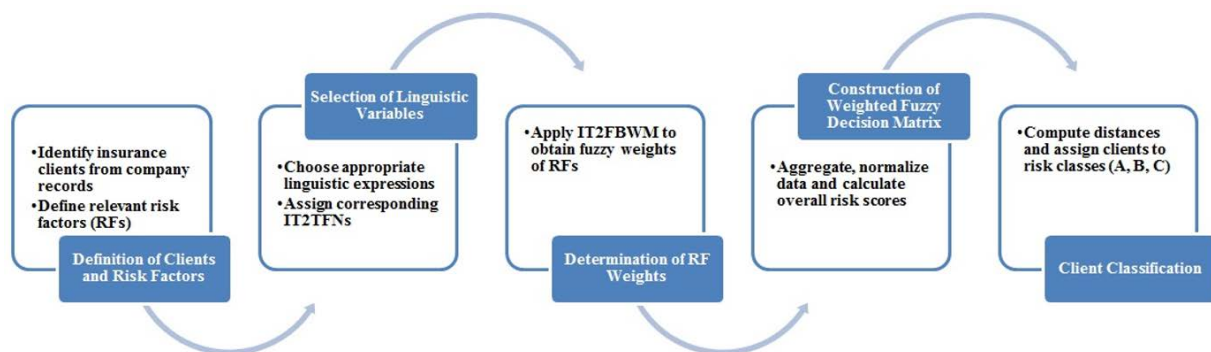


Figure 1. Proposed fuzzy classification model

2.1 Definition of the Set of Insurance Clients

Based on the available records, the set of life insurance clients of a given insurance company was defined. Generally, the clients may be represented by the set of indices $\{1, \dots, i, \dots, I\}$, where I denotes the total number of life insurance clients in the considered insurance company, and each client's index is denoted as i , with $i = 1, \dots, I$.

2.2 Definition of the Set of Evaluated RFs

Defining the set of RFs according to which the identified non-life insurance clients are evaluated can be formally represented by the set $\{1, \dots, k, \dots, K\}$. The total number of RFs is denoted as K , and k , with $k = 1, \dots, K$, is the index of the evaluation criterion. In this research, RFs were adopted from the study by Lukić et al [13]. These RFs are the total amount of incurred claims ($k = 1$), the number of claims ($k = 2$), and the loss ratio ($k = 3$).

2.3 Choosing Appropriate Linguistic Variables for Describing the Relative Importance of RFs

The relative importance of RFs can be better expressed using natural language rather than precise numerical values. A large number of studies can be found in the literature where the number of linguistic variables used is determined by DMs depending on the size and complexity of the problem. In this research, the linguistic expressions used and their corresponding IT2TFNs are as follows:

- Equal importance ($W1$): $((1, 1, 1; 1), (1, 1, 1; 1))$
- Low importance ($W2$): $((1, 3.5, 6; 1), (1.5, 3.5, 5.5; 0.75))$
- Medium importance ($W3$): $((3, 5.5, 8; 1), (3.5, 5.5, 7.5; 0.75))$
- High importance ($W4$): $((5, 7.5, 9; 1), (5.5, 7.5, 8.5; 0.75))$

There are no recommendations or guidelines on how to determine the measurement scales on which IT2TFNs are defined. In this research, the domain values of these IT2TFNs are defined on a common measurement scale. A value of 1 or 9 denotes that the relative importance of RFs is the smallest or largest, respectively.

2.4 Proposed IT2FBWM for Determining the Weight Vector

The steps for determining the weight vector are as follows:

Step 1: The relative importance of evaluation criteria was assessed by DMs. They made decisions by consensus. Predefined linguistic expressions, which were modeled by IT2TFNs, were used for this purpose. The resulting fuzzy best-to-others vector (IT2FBO), \tilde{A}_B , and fuzzy others-to-worst vector (IT2FOW), \tilde{A}_W , are presented as follows:

$$\tilde{A}_B = (\tilde{a}_{B1}, \dots, \tilde{a}_{Bk}, \dots, \tilde{a}_{BK})$$

$$\tilde{A}_W = (\tilde{a}_{W1}, \dots, \tilde{a}_{Wk}, \dots, \tilde{a}_{WK})^T$$

where, \tilde{a}_{Bk} represents the preference of the best criterion over the rest criteria. It is clear that $\tilde{a}_{BB} = ((1, 1, 1; 1), (1, 1, 1; 1))$. In addition, \tilde{a}_{Wk} represents the preference of the worst criterion over the rest of the criteria. It is clear that $\tilde{a}_{WW} = ((1, 1, 1; 1), (1, 1, 1; 1))$.

Step 2: The optimal weights of RFs, $(\tilde{\omega}_1^*, \dots, \tilde{\omega}_k^*, \dots, \tilde{\omega}_K^*)$, were obtained by using the mathematical model proposed by Wu et al. [16] below.

The objective function is given by:

$$\min \max_{k=1, \dots, K} \left\{ \left| \frac{\tilde{\omega}_B}{\tilde{\omega}_k} - \tilde{a}_{Bk} \right|, \left| \frac{\tilde{\omega}_k}{\tilde{\omega}_W} - \tilde{a}_{kW} \right| \right\} \quad (1)$$

This is subject to:

$$\text{defuzz} \left(\sum_{k=1}^K \tilde{\omega}_k = 1 \right) \quad (2)$$

$$\begin{aligned} \omega_{1k}^U &\leq \omega_{1k}^L & k &= 1, \dots, K \\ \omega_{2k}^L &\leq \omega_{3k}^U & k &= 1, \dots, K \\ \omega_{1k}^U &\leq \omega_{2k}^U \leq \omega_{3k}^U & k &= 1, \dots, K \\ \omega_{1k}^L &\leq \omega_{2k}^L \leq \omega_{3k}^L & k &= 1, \dots, K \\ \omega_{1k}^U &\geq 0 & k &= 1, \dots, K \end{aligned} \quad (3)$$

Step 3: The presented mathematical model was transformed into a linear programming model for minimizing the absolute gap as $((\varphi^*, \varphi^*, \varphi^*; 1), (\varphi^*, \varphi^*, \varphi^*; 0.9))$.

The objective function $\min \varphi^*$ is subject to:

$$\begin{aligned}
|\omega_{Bj}^U - \omega_{jk}^U a_{Bjk}^U| &\leq \varphi^* & j = 1, 2, 3; k = 1, \dots, K \\
|\omega_{jk}^U - \omega_{Wj}^U a_{Wjk}^U| &\leq \varphi^* & j = 1, 2, 3; k = 1, \dots, K \\
|\omega_{Bj}^U - \omega_{jk}^U a_{Bjk}^L| &\leq \varphi^* & j = 1, 2, 3; k = 1, \dots, K \\
|\omega_{jk}^L - \omega_{Wj}^U a_{Wjk}^L| &\leq \varphi^* & j = 1, 2, 3; k = 1, \dots, K \\
COA \sum_k \tilde{\omega}_k & & k = 1, \dots, K \\
\omega_{1k}^U &\leq \omega_{1k}^L & k = 1, \dots, K \\
\omega_{3k}^L &\leq \omega_{3k}^U & k = 1, \dots, K \\
\omega_{1k}^U &\leq \omega_{2k}^U \leq \omega_{3k}^U & k = 1, \dots, K \\
\omega_{1k}^L &\leq \omega_{2k}^L \leq \omega_{3k}^L & k = 1, \dots, K \\
\omega_{1k}^U &> 0 & k = 1, \dots, K
\end{aligned} \tag{4}$$

The weight vector of RFs, $(\tilde{\omega}_1, \dots, \tilde{\omega}_k, \dots, \tilde{\omega}_K)$, is given by solving the above model.

Step 4: The reliability of the proposed IT2FBWM was checked by calculating CR [15]:

$$CR = \frac{\delta^*}{CI} \tag{5}$$

2.5 Proposed Pareto Method with IT2TFNs

The proposed fuzzy classification model is presented below.

Step 1: The decision matrix $[x_{ik}]_{I \times K}$ was established.

$$x_{ik} = \frac{1}{T} \cdot \sum_{t=1, \dots, T} x_{ik}^t \tag{6}$$

where, x_{ik}^t represents the value of evaluation criterion k , with $k = 1, \dots, K$, for insurance client i , with $i = 1, \dots, I$, in time period t , with $t = 1, \dots, T$. The total observed period is denoted as T .

Step 2: A normalized matrix $[r_{ik}]_{I \times K}$, where r_{ik} is the normalized value of evaluation criterion k , with $k = 1, \dots, K$, for client i , with $i = 1, \dots, I$, was obtained by applying Weitenorf's linear normalization [23].

For benefit-type criteria:

$$r_{ik} = \frac{x_{ik} - x_k^{\min}}{x_k^{\max} - x_k^{\min}} \tag{7}$$

For cost-type criteria:

$$r_{ik} = \frac{x_k^{\max} - x_{ik}}{x_k^{\max} - x_k^{\min}} \tag{8}$$

where,

$$x_k^{\max} = \max_{i=1, \dots, I} x_{ik} \tag{9}$$

$$x_k^{\min} = \min_{i=1, \dots, I} x_{ik} \tag{10}$$

Step 3: The weighted normalized fuzzy decision matrix $[\tilde{z}_{ik}]_{I \times K}$ was constructed, where,

$$\tilde{z}_{ik} = \tilde{\omega}_k \cdot r_{ik} \tag{11}$$

Step 4: The overall fuzzy criterion value was calculated for each client:

$$\tilde{\rho}_i = \sum_{k=1, \dots, K} \tilde{z}_{ik} \tag{12}$$

Step 5: The maximum fuzzy value for the overall criterion was defined as:

$$\tilde{Z}^+ = ((1, 1, 1; 1), (1, 1, 1; 1))$$

Step 6: The total Hamming distance [24, 25] between the maximum fuzzy criterion value and the value for each client was calculated as:

$$\mu_i = d(\tilde{z}^+, \tilde{\rho}_{ik}) \quad (13)$$

Step 7: The distances were sorted in ascending order. Client classes were then assigned according to the rules of the conventional ABC method:

- The top 10% of clients (those with the smallest distances) were classified into Class A. These clients have the most negative impact on the company's operations. Based on this, risk management may decide not to renew their contracts for the upcoming business year or to significantly alter the contract terms.

- The next 15% of clients were classified into Class B. These clients have moderate importance for risk management. Depending on the company's market position and solvency, risk management must decide whether it is reasonable to renew contracts with clients in Class B.

- All remaining clients were classified into Class C, indicating that their associated business risk is negligible.

All mathematical operations for IT2FNs used in this research were adopted from the study by Mendel [4] and also used in some other studies [17, 20, 26].

3 Risk Classification Case Study in a Non-Life Insurance Company

The proposed model was tested using data obtained from an insurance company operating in the territory of the Republic of Serbia. To determine the relative importance of RFs, a 30-minute panel discussion was organized, involving three DMs (an executive manager, a risk manager, and a financial manager). The estimated relative importance of the considered RFs was determined by consensus. The weight vector of RFs was calculated using the proposed IT2FBWM. The values of the identified criteria were computed based on the available records. The verification of the proposed fuzzy two-stage model is presented below.

3.1 Application of IT2FBWM

This section presents the procedure for determining the weight vector of RFs. The best-to-others vector and the others-to-worst vector were provided based on the assessment of DMs. Predefined linguistic expressions were used so that:

$$\begin{aligned} \tilde{A}_B &= (W1, W2, W4) \\ \tilde{A}_W &= (W4, W3, W1) \end{aligned}$$

The linear programming model was formulated below. The objective function $\min \varphi$ is subject to:

$$\begin{aligned} \left| \frac{\omega_1}{\omega_2} - W2 \right| &\leq \varphi \\ \left| \frac{\omega_1}{\omega_3} - W4 \right| &\leq \varphi \\ \left| \frac{\omega_2}{\omega_3} - W3 \right| &\leq \varphi \\ \sum_{k=1}^K \omega_k &= 1 \\ \omega_k &\geq 0, \quad k = 1, \dots, K \end{aligned}$$

By solving the problem using the linear programming model, the following fuzzy weight vectors were obtained:

$$\begin{aligned} \tilde{\omega}_1 &= ((0.48, 0.75, 0.84; 1), (0.58, 0.75, 0.81; 0.75)) \\ \tilde{\omega}_2 &= ((0.19, 0.19, 0.19; 1), (0.19, 0.19, 0.19; 0.75)) \\ \tilde{\omega}_3 &= ((0.06, 0.06, 0.06; 1), (0.06, 0.06, 0.06; 0.75)) \end{aligned}$$

3.2 Application of Pareto with IT2TFNs

By applying the proposed algorithm (Step 1), the decision matrix was constructed and is presented in Table 1.

The normalized decision matrix (Step 2 of the proposed algorithm) is presented in Table 2.

By using the proposed algorithm (Steps 3 to 6), the overall criterion values and Hamming distances were calculated and are presented in Table 3.

The classification of clients was performed according to the proposed algorithm (Step 7) and is presented in Table 4.

Table 1. Decision matrix

i	$k = 1$	$k = 2$	$k = 3$	i	$k = 1$	$k = 2$	$k = 3$
$i = 1$	122.429	1490.285	39.9	$i = 36$	160.8	2197.741	92.65
$i = 2$	83.1	6900.273	57.52	$i = 37$	66.625	9112.814	102.1
$i = 3$	99.286	6291.243	52.3	$i = 38$	38.6	430.199	101.54
$i = 4$	88.667	28743.96	66.444	$i = 39$	57	11909.52	104.7
$i = 5$	1720.556	107086.4	25.5778	$i = 40$	92.8	1480.801	88.76
$i = 6$	125.4	20647.04	23.32	$i = 41$	434.333	59557.78	51.256
$i = 7$	518.5	66870.6	84.29	$i = 42$	79.556	3119.107	34.856
$i = 8$	603.6	84807.57	111.1	$i = 43$	318.9	28339.2	93.48
$i = 9$	133.9	9466.359	45.51	$i = 44$	74.556	5197.569	105.189
$i = 10$	119.2	7107.967	33.89	$i = 45$	46.7	333.065	31.82
$i = 11$	371.9	20288.36	56.08	$i = 46$	107.778	5901.342	107.233
$i = 12$	142	9758.237	73.843	$i = 47$	91.75	2799.49	113.512
$i = 13$	73.1	11083.99	32.96	$i = 48$	46.25	3973.718	34.037
$i = 14$	442.8	36562.95	67.33	$i = 49$	57.625	1037	24.387
$i = 15$	377.4	67572.6	36.61	$i = 50$	237.9	26435.16	34.03
$i = 16$	70.556	1164.984	36.367	$i = 51$	148.3	18536.5	56.57
$i = 17$	59	2384.316	45.329	$i = 52$	150	18135.21	44.93
$i = 18$	40.286	853.945	46.986	$i = 53$	149.9	20550.03	20.81
$i = 19$	37	577.081	86.657	$i = 54$	501.625	49877.26	73.838
$i = 20$	92.5	2569.648	25.99	$i = 55$	170.9	13161.94	81.71
$i = 21$	42.875	5196.166	63.25	$i = 56$	376.3	11038.66	54.52
$i = 22$	293.7	4699.427	107.03	$i = 57$	155.556	9717.693	95.278
$i = 23$	259.375	3479.048	33.625	$i = 58$	396.6	25544.32	30.22
$i = 24$	54	3151.453	23.35	$i = 59$	53.222	8554.702	114.767
$i = 25$	36.571	990.76	102.4	$i = 60$	96.111	6099.25	78
$i = 26$	190.375	15877.32	18.75	$i = 61$	410.375	3320.925	81.537
$i = 27$	123.3	13430.43	35.72	$i = 62$	105.5	8803.758	44.26
$i = 28$	120.571	1574.826	37.2	$i = 63$	116.5	6957.913	47.6
$i = 29$	64.571	9847.271	56.4	$i = 64$	69.5	2888.851	29.54
$i = 30$	53.625	1713.908	27.137	$i = 65$	392.287	4667.092	54.943
$i = 31$	108.4	811.355	128.44	$i = 66$	66.286	751.369	20.243
$i = 32$	78.111	9108.699	44.433	$i = 67$	40.5	3092.752	13.725
$i = 33$	45.556	1189.969	55.178	$i = 68$	53.375	4422.564	36.25
$i = 34$	42.286	5390.493	28.043	$i = 69$	3055.286	56979.1	27.9
$i = 35$	50.111	1409.97	66.122	$i = 70$	103.4	6471.038	26.15

Table 2. Normalized decision matrix

<i>i</i>	<i>k</i> = 1	<i>k</i> = 2	<i>k</i> = 3	<i>i</i>	<i>k</i> = 1	<i>k</i> = 2	<i>k</i> = 3
<i>i</i> = 1	0.028	0.011	0.772	<i>i</i> = 36	0.041	0.017	0.312
<i>i</i> = 2	0.015	0.062	0.618	<i>i</i> = 37	0.010	0.082	0.230
<i>i</i> = 3	0.021	0.056	0.664	<i>i</i> = 38	0.001	0.001	0.234
<i>i</i> = 4	0.017	0.266	0.540	<i>i</i> = 39	0.007	0.108	0.207
<i>i</i> = 5	0.558	1.000	0.897	<i>i</i> = 40	0.019	0.011	0.346
<i>i</i> = 6	0.029	0.190	0.916	<i>i</i> = 41	0.132	0.555	0.673
<i>i</i> = 7	0.160	0.623	0.385	<i>i</i> = 42	0.014	0.026	0.816
<i>i</i> = 8	0.188	0.791	0.151	<i>i</i> = 43	0.094	0.262	0.305
<i>i</i> = 9	0.032	0.086	0.723	<i>i</i> = 44	0.013	0.046	0.203
<i>i</i> = 10	0.027	0.063	0.824	<i>i</i> = 45	0.003	0.000	0.842
<i>i</i> = 11	0.111	0.187	0.631	<i>i</i> = 46	0.024	0.052	0.185
<i>i</i> = 12	0.035	0.088	0.476	<i>i</i> = 47	0.018	0.023	0.130
<i>i</i> = 13	0.012	0.101	0.832	<i>i</i> = 48	0.003	0.034	0.823
<i>i</i> = 14	0.135	0.339	0.533	<i>i</i> = 49	0.007	0.007	0.907
<i>i</i> = 15	0.113	0.630	0.801	<i>i</i> = 50	0.067	0.245	0.823
<i>i</i> = 16	0.011	0.008	0.803	<i>i</i> = 51	0.037	0.171	0.627
<i>i</i> = 17	0.007	0.019	0.724	<i>i</i> = 52	0.038	0.167	0.728
<i>i</i> = 18	0.001	0.005	0.710	<i>i</i> = 53	0.038	0.189	0.938
<i>i</i> = 19	0.000	0.002	0.364	<i>i</i> = 54	0.154	0.464	0.476
<i>i</i> = 20	0.019	0.021	0.893	<i>i</i> = 55	0.044	0.120	0.407
<i>i</i> = 21	0.002	0.046	0.568	<i>i</i> = 56	0.113	0.100	0.644
<i>i</i> = 22	0.085	0.041	0.187	<i>i</i> = 57	0.039	0.088	0.289
<i>i</i> = 23	0.074	0.029	0.827	<i>i</i> = 58	396.6	25544.32	30.22
<i>i</i> = 24	0.006	0.026	0.916	<i>i</i> = 59	53.222	8554.702	114.767
<i>i</i> = 25	0.000	0.006	0.227	<i>i</i> = 60	96.111	6099.25	78
<i>i</i> = 26	0.051	0.146	0.956	<i>i</i> = 61	410.375	3320.925	81.537
<i>i</i> = 27	0.029	0.123	0.808	<i>i</i> = 62	105.5	8803.758	44.26
<i>i</i> = 28	0.028	0.012	0.795	<i>i</i> = 63	116.5	6957.913	47.6
<i>i</i> = 29	0.009	0.089	0.628	<i>i</i> = 64	69.5	2888.851	29.54
<i>i</i> = 30	0.006	0.013	0.883	<i>i</i> = 65	392.287	4667.092	54.943
<i>i</i> = 31	0.024	0.004	0.000	<i>i</i> = 66	66.286	751.369	20.243
<i>i</i> = 32	0.014	0.082	0.732	<i>i</i> = 67	40.5	3092.752	13.725
<i>i</i> = 33	0.003	0.008	0.639	<i>i</i> = 68	53.375	4422.564	36.25
<i>i</i> = 34	0.002	0.047	0.875	<i>i</i> = 69	3055.286	56979.1	27.9
<i>i</i> = 35	0.004	0.010	0.543	<i>i</i> = 70	103.4	6471.038	26.15

Table 3. Overall criterion values and Hamming distances

i	$\tilde{\rho}_i$	M_i	i	$\tilde{\rho}_i$	M_i
$i = 1$	$(0.062, 0.070, 0.072; 1),$ $(0.065, 0.070, 0.071; 0.75)$	0.931	$i = 36$	$(0.042, 0.053, 0.057; 1),$ $(0.046, 0.053, 0.055; 0.75)$	0.949
$i = 2$	$(0.056, 0.060, 0.062; 1),$ $(0.058, 0.070, 0.061; 0.75)$	0.940	$i = 37$	$(0.034, 0.037, 0.038; 1),$ $(0.035, 0.037, 0.037; 0.75)$	0.963
$i = 3$	$(0.060, 0.066, 0.068; 1),$ $(0.062, 0.066, 0.067; 0.75)$	0.935	$i = 38$	$(0.015, 0.015, 0.015; 1),$ $(0.015, 0.015, 0.015; 0.75)$	0.985
$i = 4$	$(0.091, 0.096, 0.097; 1),$ $(0.093, 0.096, 0.097; 0.75)$	0.905	$i = 39$	$(0.036, 0.038, 0.039; 1),$ $(0.037, 0.038, 0.039; 0.75)$	0.962
$i = 5$	$(0.512, 0.662, 0.712; 1),$ $(0.567, 0.662, 0.696; 0.75)$	0.358	$i = 40$	$(0.032, 0.037, 0.038; 1),$ $(0.034, 0.037, 0.038; 0.75)$	0.964
$i = 6$	$(0.105, 0.113, 0.116; 1),$ $(0.108, 0.113, 0.115; 0.75)$	0.888	$i = 41$	$(0.209, 0.245, 0.256; 1),$ $(0.222, 0.245, 0.253; 0.75)$	0.760
$i = 7$	$(0.218, 0.261, 0.276; 1),$ $(0.234, 0.261, 0.271; 0.75)$	0.745	$i = 42$	$(0.061, 0.065, 0.066; 1),$ $(0.062, 0.065, 0.065; 0.75)$	0.936
$i = 8$	$(0.250, 0.300, 0.317; 1),$ $(0.268, 0.300, 0.312; 0.75)$	0.707	$i = 43$	$(0.113, 0.138, 0.147; 1),$ $(0.122, 0.138, 0.144; 0.75)$	0.865
$i = 9$	$(0.075, 0.084, 0.087; 1),$ $(0.078, 0.084, 0.086; 0.75)$	0.917	$i = 44$	$(0.027, 0.030, 0.031; 1),$ $(0.028, 0.030, 0.031; 0.75)$	0.970
$i = 10$	$(0.075, 0.082, 0.085; 1),$ $(0.077, 0.082, 0.084; 0.75)$	0.919	$i = 45$	$(0.052, 0.053, 0.053; 1),$ $(0.052, 0.053, 0.053; 0.75)$	0.947
$i = 11$	$(0.127, 0.157, 0.167; 1),$ $(0.138, 0.157, 0.163; 0.75)$	0.847	$i = 46$	$(0.032, 0.039, 0.041; 1),$ $(0.035, 0.039, 0.040; 0.75)$	0.962
$i = 12$	$(0.062, 0.072, 0.075; 1),$ $(0.066, 0.072, 0.074; 0.75)$	0.930	$i = 47$	$(0.021, 0.026, 0.028; 1),$ $(0.023, 0.026, 0.027; 0.75)$	0.975
$i = 13$	$(0.075, 0.078, 0.079; 1),$ $(0.076, 0.078, 0.079; 0.75)$	0.922	$i = 48$	$(0.057, 0.058, 0.059; 1),$ $(0.058, 0.058, 0.058; 0.75)$	0.942
$i = 14$	$(0.161, 0.197, 0.209; 1),$ $(0.174, 0.197, 0.205; 0.75)$	0.808	$i = 49$	$(0.059, 0.061, 0.062; 1),$ $(0.060, 0.061, 0.061; 0.75)$	0.939
$i = 15$	$(0.222, 0.252, 0.263; 1),$ $(0.233, 0.252, 0.259; 0.75)$	0.752	$i = 50$	$(0.128, 0.146, 0.152; 1),$ $(0.135, 0.146, 0.150; 0.75)$	0.857
$i = 16$	$(0.055, 0.058, 0.059; 1),$ $(0.056, 0.058, 0.059; 0.75)$	0.942	$i = 51$	$(0.088, 0.098, 0.101; 1),$ $(0.091, 0.098, 0.100; 0.75)$	0.904
$i = 17$	$(0.051, 0.053, 0.053; 1),$ $(0.051, 0.053, 0.053; 0.75)$	0.948	$i = 52$	$(0.093, 0.104, 0.107; 1),$ $(0.097, 0.104, 0.106; 0.75)$	0.898
$i = 18$	$(0.044, 0.044, 0.045; 1),$ $(0.044, 0.044, 0.045; 0.75)$	0.956	$i = 53$	$(0.110, 0.120, 0.124; 1),$ $(0.114, 0.120, 0.123; 0.75)$	0.881

i	$\tilde{\rho}_i$	M_i	i	$\tilde{\rho}_i$	M_i
$i = 19$	$\left(\begin{array}{l} (0.022, 0.022, 0.022; 1), \\ (0.022, 0.022, 0.022; 0.75) \end{array} \right)$	0.978	$i = 54$	$\left(\begin{array}{l} (0.191, 0.232, 0.246; 1), \\ (0.206, 0.232, 0.242; 0.75) \end{array} \right)$	0.773
$i = 20$	$\left(\begin{array}{l} (0.066, 0.071, 0.073; 1), \\ (0.068, 0.071, 0.073; 0.75) \end{array} \right)$	0.929	$i = 55$	$\left(\begin{array}{l} (0.069, 0.081, 0.085; 1), \\ (0.073, 0.081, 0.083; 0.75) \end{array} \right)$	0.921
$i = 21$	$\left(\begin{array}{l} (0.044, 0.044, 0.045; 1), \\ (0.044, 0.044, 0.045; 0.75) \end{array} \right)$	0.956	$i = 56$	$\left(\begin{array}{l} (0.112, 0.142, 0.152; 1), \\ (0.123, 0.142, 0.149; 0.75) \end{array} \right)$	0.862
$i = 22$	$\left(\begin{array}{l} (0.060, 0.083, 0.091; 1), \\ (0.068, 0.083, 0.088; 0.75) \end{array} \right)$	0.920	$i = 57$	$\left(\begin{array}{l} (0.053, 0.064, 0.067; 1), \\ (0.057, 0.064, 0.066; 0.75) \end{array} \right)$	0.938
$i = 23$	$\left(\begin{array}{l} (0.091, 0.111, 0.117; 1), \\ (0.098, 0.111, 0.115; 0.75) \end{array} \right)$	0.892	$i = 58$	$\left(\begin{array}{l} (0.153, 0.186, 0.196; 1), \\ (0.165, 0.186, 0.193; 0.75) \end{array} \right)$	0.819
$i = 24$	$\left(\begin{array}{l} (0.063, 0.064, 0.065; 1), \\ (0.063, 0.064, 0.065; 0.75) \end{array} \right)$	0.936	$i = 59$	$\left(\begin{array}{l} (0.024, 0.026, 0.026; 1), \\ (0.025, 0.026, 0.026; 0.75) \end{array} \right)$	0.974
$i = 25$	$\left(\begin{array}{l} (0.015, 0.015, 0.015; 1), \\ (0.015, 0.015, 0.015; 0.75) \end{array} \right)$	0.985	$i = 60$	$\left(\begin{array}{l} (0.046, 0.051, 0.053; 1), \\ (0.048, 0.051, 0.053; 0.75) \end{array} \right)$	0.949
$i = 26$	$\left(\begin{array}{l} (0.109, 0.123, 0.128; 1), \\ (0.115, 0.123, 0.126; 0.75) \end{array} \right)$	0.879	$i = 61$	$\left(\begin{array}{l} (0.089, 0.123, 0.134; 1), \\ (0.102, 0.123, 0.130; 0.75) \end{array} \right)$	0.882
$i = 27$	$\left(\begin{array}{l} (0.086, 0.093, 0.096; 1), \\ (0.088, 0.093, 0.095; 0.75) \end{array} \right)$	0.908	$i = 62$	$\left(\begin{array}{l} (0.070, 0.076, 0.078; 1), \\ (0.072, 0.076, 0.078; 0.75) \end{array} \right)$	0.925
$i = 28$	$\left(\begin{array}{l} (0.063, 0.071, 0.073; 1), \\ (0.066, 0.071, 0.072; 0.75) \end{array} \right)$	0.930	$i = 63$	$\left(\begin{array}{l} (0.067, 0.074, 0.076; 1), \\ (0.069, 0.074, 0.076; 0.75) \end{array} \right)$	0.927
$i = 29$	$\left(\begin{array}{l} (0.059, 0.062, 0.062; 1), \\ (0.060, 0.062, 0.062; 0.75) \end{array} \right)$	0.939	$i = 64$	$\left(\begin{array}{l} (0.062, 0.064, 0.065; 1), \\ (0.063, 0.066, 0.065; 0.75) \end{array} \right)$	0.936
$i = 30$	$\left(\begin{array}{l} (0.058, 0.060, 0.060; 1), \\ (0.059, 0.060, 0.060; 0.75) \end{array} \right)$	0.941	$i = 65$	$\left(\begin{array}{l} (0.103, 0.135, 0.145; 1), \\ (0.115, 0.135, 0.142; 0.75) \end{array} \right)$	0.870
$i = 31$	$\left(\begin{array}{l} (0.012, 0.019, 0.021; 1), \\ (0.015, 0.019, 0.020; 0.75) \end{array} \right)$	0.982	$i = 66$	$\left(\begin{array}{l} (0.062, 0.065, 0.066; 1), \\ (0.063, 0.065, 0.065; 0.75) \end{array} \right)$	0.936
$i = 32$	$\left(\begin{array}{l} (0.066, 0.070, 0.071; 1), \\ (0.068, 0.070, 0.071; 0.75) \end{array} \right)$	0.931	$i = 67$	$\left(\begin{array}{l} (0.066, 0.066, 0.066; 1), \\ (0.066, 0.066, 0.066; 0.75) \end{array} \right)$	0.934
$i = 33$	$\left(\begin{array}{l} (0.041, 0.042, 0.042; 1), \\ (0.042, 0.042, 0.042; 0.75) \end{array} \right)$	0.958	$i = 68$	$\left(\begin{array}{l} (0.058, 0.060, 0.060; 1), \\ (0.059, 0.060, 0.060; 0.75) \end{array} \right)$	0.941
$i = 34$	$\left(\begin{array}{l} (0.062, 0.063, 0.063; 1), \\ (0.063, 0.063, 0.063; 0.75) \end{array} \right)$	0.937	$i = 69$	$\left(\begin{array}{l} (0.633, 0.903, 0.993; 1), \\ (0.733, 0.903, 0.963; 0.75) \end{array} \right)$	0.133
$i = 35$	$\left(\begin{array}{l} (0.037, 0.038, 0.038; 1), \\ (0.037, 0.038, 0.038; 0.75) \end{array} \right)$	0.962	$i = 70$	$\left(\begin{array}{l} (0.075, 0.081, 0.083; 1), \\ (0.077, 0.081, 0.082; 0.75) \end{array} \right)$	0.920

Table 4. Client classes

i	M_i	Class	i	M_i	Class	i	M_i	Class
$i = 69$	0.133	A	$i = 51$	0.904	C	$i = 30; i = 68$	0.941	C
$i = 5$	0.358	A	$i = 4$	0.905	C	$i = 16; i = 48$	0.942	C
$i = 8$	0.707	A	$i = 27$	0.908	C	$i = 45$	0.947	C
$i = 7$	0.745	A	$i = 9$	0.917	C	$i = 17$	0.948	C
$i = 15$	0.752	A	$i = 10$	0.919	C	$i = 36; i = 60$	0.949	C
$i = 41$	0.760	A	$i = 22; i = 70$	0.920	C	$i = 18; i = 21$	0.956	C
$i = 54$	0.773	B	$i = 55$	0.921	C	$i = 33$	0.958	C
$i = 14$	0.808	B	$i = 13$	0.922	C	$i = 35; i = 39; i = 46$	0.962	C
$i = 58$	0.819	B	$i = 62$	0.925	C	$i = 37$	0.963	C
$i = 11$	0.847	B	$i = 63$	0.927	C	$i = 40$	0.964	C
$i = 50$	0.857	B	$i = 20$	0.929	C	$i = 44$	0.970	C
$i = 56$	0.862	B	$i = 12; i = 28$	0.930	C	$i = 59$	0.974	C
$i = 43$	0.865	B	$i = 1; i = 32$	0.931	C	$i = 47$	0.975	C
$i = 65$	0.870	B	$i = 67$	0.934	C	$i = 19$	0.978	C
$i = 26$	0.879	B	$i = 3$	0.935	C	$i = 31$	0.982	C
$i = 53$	0.881	B	$i = 24; i = 42; i = 64; i = 66$	0.936	C	$i = 25; i = 38$	0.985	C
$i = 61$	0.882	B	$i = 34$	0.937	C			
$i = 6$	0.888	B	$i = 57$	0.938	C			
$i = 23$	0.892	B	$i = 29; i = 49$	0.939	C			
$i = 52$	0.898	B	$i = 2$	0.940	C			

Based on the obtained results, the risk management of the considered insurance company can make decisions regarding contract renewal with clients in a way that contributes to reducing the company's business risk.

4 Discussion of the Obtained Results

Based on the obtained results, it can be concluded that the smallest number of clients belongs to Class A, followed by Class B, while the majority of clients fall into Class C, as shown in Figure 2.

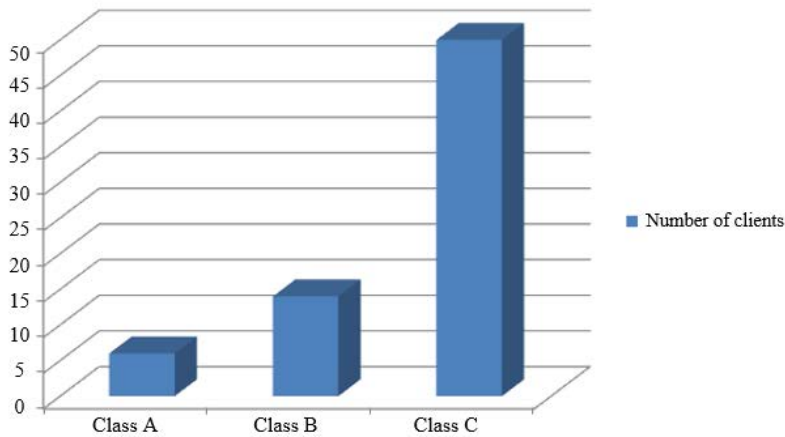


Figure 2. Distribution of clients according to risk classes (A, B, and C)

As shown in Figure 2, the largest number of clients belongs to Class C. This essentially means that most clients are stable business partners. There are a total of 50 such clients. A significantly smaller number falls into the other two client categories. Class B (14 clients) includes clients whose status is debatable, and several aspects should be considered before renewing their contracts. The smallest number of clients belongs to Class A (six clients), who can definitely have a negative impact on the company's operations, i.e., they are not reliable business partners. The correlation coefficient calculated between the values for each criterion individually can be graphically represented, as shown in Figure 3.

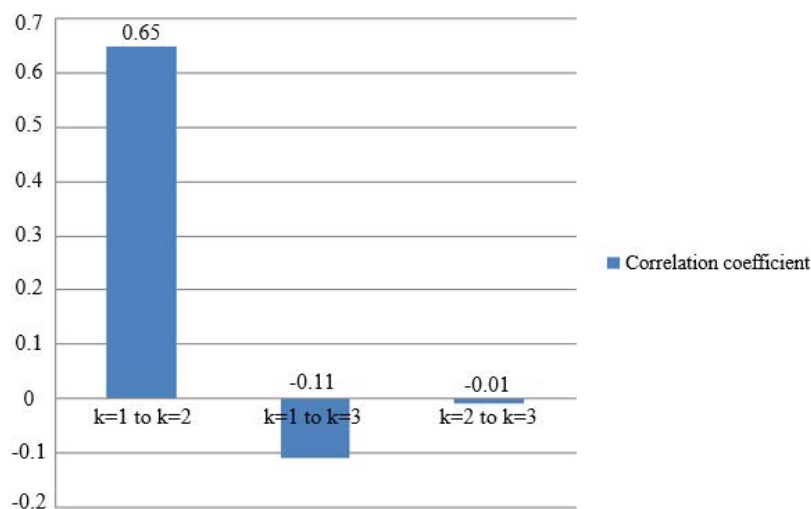


Figure 3. Graphical representation of the correlation between evaluation criteria

As shown in Figure 3, there is a certain correlation between the total amount of incurred claims ($k = 1$) and the number of claims ($k = 2$), which is quite logical. However, even this correlation is not statistically strong. There is absolutely no correlation in all other cases, that is, when the correlation coefficient is calculated between the total amount of incurred claims ($k = 1$) and the loss ratio ($k = 3$), as well as between the number of claims ($k = 2$) and the loss ratio ($k = 3$).

5 Conclusion

One of the most important risk management tasks in an insurance company is the reduction of business risk in the domain of non-life insurance. This issue can be addressed, among other approaches, by assessing the risk of contract renewal at the level of each individual client. Such decisions directly contribute to increasing profitability and ensuring long-term sustainability of the company's operations. The problem becomes significantly more complex in an uncertain environment that is rapidly and continuously changing.

The main advantages of the proposed two-stage fuzzy model can be summarized as follows:

- The relative importance of the considered RFs was described using natural language and modeled through IT2TFNs.
- The weight vector of RFs was determined in an exact manner by applying FBWM.
- Client classification was performed using the proposed fuzzy Pareto analysis.
- The risk assessment process becomes more efficient and easier to implement.
- The results of the proposed two-stage fuzzy model are clear and interpretable by non-experts.
- Changes in the number of RFs as well as their relative importance can be easily integrated into the model.
- The model can be readily implemented in any insurance company, thereby contributing to improved performance and risk control.

The main limitation of the proposed two-stage fuzzy model lies in the identification of RFs and the assessment of their relative importance. Future research should involve benchmarking the obtained results against those from other insurance companies operating in the non-life insurance sector.

Data Availability

The data used to support the research findings are available from the corresponding author upon request.

Conflicts of Interest

The authors confirm that there are no conflicts of interest related to the research or its publication.

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