A Consolidated MCDM Framework for Overall Performance Assessment of Listed Insurance Companies Based on Ranking Strategies

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Abstract

The main objective of this study is to analyze the performance of non-life insurance companies operating in the Turkish insurance industry with a hybrid model including Pythagorean Fuzzy Analytic Hierarchy Process (PFAHP) and Multi-Attributive Ideal-Real Comparative Analysis (MAIRCA) methods. For this purpose, the performance assessment indicators, consisting of fourteen sub-criteria in three dimensions are taken into account for comparing five insurance companies traded on the Borsa Istanbul (BIST) over five consecutive years (2015 to 2019). Subsequently, year-wise rankings are aggregated using the Borda count (BC) procedure. The results of PFAHP indicate that service network is the most important main criterion (dimension) for performance assessment of non-life insurance companies, followed by stock market performance and financial ratios that come in the second and third ranks, respectively. Furthermore, the results of MAIRCA based on BC procedure reveal that Halk Sigorta, a state-owned insurance company, is the most successful company in terms of selected performance indicators in the period examined. A comprehensive sensitivity analysis is performed in order to test stability and the robustness of the results from the proposed framework, and the results of sensitivity analysis confirms the rationality and robustness of the suggested integrated MCDM framework. As a result, the suggested assessment framework can be applied by different decision-making groups in the industry as a valuable and practical decision-making tool for monitoring and improving the performance of insurance companies. Finally, some of managerial implications are also discussed.

Keywords Turkish insurance sector · Non-life insurance companies · Performance analysis · Pythagorean fuzzy AHP · MAIRCA · Borda count

Abbreviations

AHP	Analytic hierarchy process
BWM	Best worst method
BC	Borda count

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CoCoSo   Combined compromise solution
COPRAS   Complex proportional assessment
CRADIS   Compromise ranking of alternatives from distance to ideal solution
DEA   Data envelopment analysis
DEMATEL   Decision making trial and evaluation laboratory
DANP   DEMATEL-based analytic network process
FUCOM   Full consistency method
FAHP   Fuzzy analytic hierarchy process
FSs   Fuzzy sets
GRA   Grey relational analysis
IFSs   Intuitionistic fuzzy sets
LBWA   Level based weight assessment
MOORA   Multi objective optimization on the basis of ration analysis
MAIRCA   Multi-attributive ideal-real comparative analysis
OCRA   Operational competitiveness ratings
PIPRECIA   PIvot pairwise relative criteria importance assessment
PIV   Proximity indexed value
PFAHP   Pythagorean fuzzy analytic hierarchy process
PFSs   Pythagorean fuzzy sets
TOPSIS   Technique for order performance by similarity to ideal solution
VIKOR   VlseKriterijuska Optimizacija I Komoromisno Resenje

1 Introduction

Companies operating in the fields of life and non-life insurance generally undertake to cover the loss of the insured against a predetermined event in return for a certain premium or fee under an insurance policy.

Wars, infectious diseases, natural disasters, economic or financial crises that have emerged in recent years have deeply affected social and economic life around the world. Therefore, in line with these developments, there has been a significant increase in the uncertainty and risks that individuals and companies are exposed to, which has triggered the need for insurance companies (Ćurak et al., 2009; Magee et al., 2019; Shen et al., 2017; Xiazi & Shabir, 2022).

Although banks are more dominant financial institutions in financial service intermediation compared to other financial intermediaries, it is possible to say that insurance companies play an increasingly vital role in the process of financial intermediation. Indeed, insurance companies, one of the most dynamic financial intermediaries of the financial system, play a very important role in the effective functioning of financial markets and make significant contributions to the growth and development of every economy through the products and services they offer to their customers (Biener et al., 2016; Ćurak et al., 2009; Oscar Akotey et al., 2013; Suvvari et al., 2019; Yang, 2006).

Insurance companies that collect funds from individuals and other companies by issuing insurance policies mediate the transformation of the collected funds into real investments. Additionally, insurance companies, which act as a risk management mechanism for economic units such as individuals and real sector companies, also contribute to the establishment of financial stability in financial markets (Chen & Lu, 2015; Khan & Noreen, 2014; Torbati & Sayadi, 2018).

The performance assessment of insurance companies has attracted the attention of many researchers due to its significant impact on economic activities and human life. Analysing the performance of insurance companies is critical to the stability of the economies of both developed and developing countries.

While some insurance companies achieve higher performance and profitability, others face structural problems. Since any problem that may arise in financial service intermediation within a financial system has adverse effects on individuals, shareholders, real sector companies, and the overall economy, the performance of financial institutions such as insurance companies and other intermediaries (banks, mutual funds, etc.) in the financial service network should be measured and evaluated systematically (Asadi & Moghri, 2016; Aytekin & Karamaşa, 2017; Seçme et al., 2009; Suvvari et al., 2019). Indeed, the efficiency of insurance companies' financial intermediation role and the sustainability of their activities can be associated with the regular analysis of the performance of these companies in terms of various indicators and the detailed examination of the analysis results obtained.

1.1 Objectives and Contributions

Overall performance assessment, which has an impact on all operational activities of insurance companies, is a key tool for achieving sustainable competitive advantage and improving performance in the insurance market, which has a competitive and dynamic structure.

Given that the ranking issue in the insurance industry is one of the most critical optimization problems in the MCDM literature, our paper aims to address the performance evaluation issue for insurance companies. To this end, five listed insurers whose shares are traded on BIST in the 2015–2019 period are determined. Following a detailed literature review, fourteen evaluation criteria are defined in three different dimensions such as financial ratios, service network and stock market performance. The evaluation criteria selected for performance assessment offer a practical framework for all stakeholders involved in the insurance industry (managers, policyholders, agents, banks, authorities, etc.) to make more effective, robust, and reliable decisions.

The present study also proposes the use of a new integrated approach that comprises PFAHP and MAIRCA procedures that will allow decision-makers to solve the problem with many conflicting criteria and express their ambiguous

views in the decision-making environment. The main reason for combining these two methods is to integrate the advantages of both approaches into the performance assessment process, as outlined below. The presented MCDM approach is a novel performance analysis procedure and can also provide a very comprehensive assessment methodology that can be utilized as a mathematical tool to assess insurers' overall performance. Consequently, the suggested PFSHP-MAIRCA tool can serve as decision support to various decision-makers in the insurance industry in identifying a reliable, realistic, and applicable methodological framework.

The main contributions of this study to the insurance literature are as follows:

- The current article is the first study to address the overall performance assessment of publicly quoted companies in the insurance market in terms of financial ratios, service network and stock market performance. Thus, it proposes a novel set of criteria for performance analysis and assessment in the insurance sector and the suggested criteria set can meet the DMs' requirements related to identifying a reliable, realistic, and practical methodological framework.
- A novel integrated MCDM approach encompassing PFAHP and MAIRCA procedures is proposed.
- A real-time case study is performed for assessment of listed non-life insurers' overall performance in Turkish insurance market.
- Unlike other studies in the literature, the present paper merges the 5-year ranking results of listed non-life insurance companies according to the BC principle, which makes an important scientific contribution to the literature.

1.2 Motivation for Using PFSs and PFAHP

The concept of fuzzy sets (FSs) was introduced by Zadeh (1965) as a valuable tool for taking the vagueness and impreciseness of subjective evaluations into account. According to classical fuzzy set theory, an element is either a member of a set or not. Thus, while FSs are capable of expressing the degree of membership (μ) of an element, they are insufficient to express its degree of non-membership (ν) (Buyukozkan & Gocer, 2019). To overcome the shortcoming regarding the ν in classical FSs, Atanassov (1986) extended the classical FSs and developed Intuitionistic Fuzzy Sets (IFSs), which take into account both the μ and the ν of an element. The total value for the parameters μ and ν in IFSs should be between 0 and 1 or equal to these values (Shen et al., 2018). However, in some problems, the total value of these parameters obtained through the experts may be greater than 1. This situation is not appropriately addressed in the IFSs (Garg & Chen, 2020). To address this limitation, Yager (2013) developed the Pythagorean Fuzzy Sets (PFSs), which are an extension of the IFSs, by stretching the condition of $\mu + \nu \leq 1$ to $\mu^2 + \nu^2 \leq 1$ (Kutlu Gündoğdu & Kahraman, 2020). Consequently, the main difference between IFSs and PFSs is that the latter can deal with more information in the fuzzy

environment (Garg, 2016; Garg & Chen, 2020; Lin et al., 2021). In other words, PFSs provide decision-makers with greater flexibility in expressing their opinions concerning the vagueness and impreciseness of the considered decision-making problem (Ilbahar et al., 2018; Lahane & Kant, 2023).

In the present paper, the PFAHP approach, obtained by integrating PFSs into the AHP method, is utilized to prioritize the evaluation criteria. Compared with traditional Analytic Hierarchy Process (AHP) and FAHP, this approach has a variety of advantages. It can better handle the uncertainty of decision-making environment (Ayyildiz et al., 2021; Buyukozkan & Gocer, 2019). Additionally, as the decision problem gets more complicated, it provides more consistent, reliable and robust outcomes (Başaran et al., 2023; Karasan et al., 2019). Besides, it can easily reduce uncertainty in the decision-making process by providing more flexibility to decision-makers. This feature makes it easier for decision-makers to achieve clearer solutions (Ayyildiz & Taskin Gumus, 2021).

1.3 Motivation for Using MAIRCA

The MAIRCA approach is responsible for the ranking of decision alternatives. The advantages of employing the MAIRCA algorithm based on the comparison of theoretical and empirical alternative ratings (Pamučar et al., 2014) are: (1) this algorithm is not influenced by the rank reversal problem (Pamucar et al., 2018); (2) since its mathematical frame remains the same irrespective of the number of decision alternatives and evaluation criteria, it is considered to be a feasible choice for MCDM problems involving a large number of alternatives and criteria (Boral et al., 2020; Gülin Feryal & Muzaffer Bertan, 2019); (3) it provides a convenient and practical approach for the decision maker, as it does not require advanced mathematical knowledge and has high solution stability in response to changes in the character and structure of the criteria (Pamucar et al., 2022; Pamučar et al., 2017); (4) The MAIRCA algorithm, which has a more straightforward and more flexible normalization technique, helps decision makers obtain faster, reliable and robust results (Ecer, 2022); (5) this technique can be very successfully combined with a variety of MCDM approaches (Kaya, 2020); and (6) it provides a more objective rankings based on the predefined dominance threshold, which makes it easier for decision-makers to make a final decision (Zolfani et al., 2021).

1.4 Organization of the Study

The present paper is structured as follows: A brief review of recent literature on both the performance evaluation of insurance companies and the applications of PFAHP and MAIRCA methods in MCDM problems is presented in Sect. 2. The suggested hybrid methodology for overall performance assessment is described in detail in Sect. 3. Section 4 provides the findings of the suggested hybrid methodology and

sensitivity analyses. The managerial implications of current paper are also discussed in this section. Finally, Sect. 5 presents the conclusion, limitations, and suggestions for future research.

2 Literature Review

The literature review is organized into four sections. Past studies that assess performance and efficiency by applying MCDM techniques in the insurance market are overviewed in the first subsection. In the second and third subsections, the literature on the MCDM techniques that constitute the suggested performance evaluation approach has been examined. In the last subsection, research gaps regarding previous studies in the literature are identified.

2.1 MCDM Techniques in Insurance Market

Recently, researchers from different disciplines have integrated MCDM tools into the solution process of many multi-criteria decision-making problems. In addition to this, various dynamics such as significant changes and transformations in the markets, advances in science and technology, increasing competition, trade wars have made it important to measure and evaluate the performance of companies concerning the conflicting criteria, which has increased the interest in the use of MCDM tools in this field. Although most of the studies in the performance evaluation literature focus on manufacturing companies and banks, it is noteworthy that the number of studies conducted to evaluate the performance of insurance companies have tended to increase in recent years. Thus, some of the studies related to the performance assessment of the insurance companies are summarized as follows.

The Data Envelopment Analysis (DEA) method is one of the methods frequently used to evaluate the performance of insurance companies in the literature (Akhtar, 2018; Al-Amri et al. 2012; Barros et al., 2005; Ilyas & Rajasekaran, 2019). For example, Hong and Kim (2001) suggested a hybrid methodology combining DEA with a self-organizing map approaches for assessing the performance of twenty-nine life insurance companies operating in South Korea. Yang (2006) used a two-stage DEA model for the production and investment performances of seventy-two insurance companies operating in Canada during 1998. Davutyan and Klumpes (2008) utilized the DEA methodology for efficiency comparison of 188 life and 284 non-life insurers from seven European countries (France, Germany, Italy, Netherlands, Spain, Switzerland, and the UK) over the period 1996–2002. Eling and Luhnen (2010) compared the efficiency performance of 6462 insurers from 36 countries by using the DEA approach from 2002 to 2006. Khan and Noreen (2014) analyzed the performance of seventeen insurance companies operating in Pakistan between 2006 and 2010 by using the DEA technique. Zimková (2015) utilized the DEA approach for assessing and ranking thirteen Slovak insurance companies by considering their efficiency scores in the year 2013. Eling and Jia

(2019) investigated the efficiency and profitability relationship in the life and nonlife insurance industries using Stochastic Frontier Analysis, the DEA and regression analyses. Wanke and Barros (2016) applied the DEA and data mining techniques of insurance companies in Brazil over 19-years for efficiency measurement. Tone et al. (2019) examined the effect of investment assets on the performance of insurance companies in Malaysia from 2008 to 2016 by a dynamic two-stage network DEA model. Almulhim (2019) employed a two-stage DEA to assess the efficiency scores of thirty-three listed insurance companies in Saudi Arabia during 2014–2017. In another study focusing on the Saudi Arabian insurance industry, Benyoussef and Hemrit (2019) used the DEA method for comparing the efficiency of twenty-three insurance companies. Gharizadeh Beiragh et al. (2020) proposed an integrated MCDM model comprising AHP, principal component analysis and DEA methods to evaluate and rank the sustainability performance of fourteen Iranian insurance companies for the year 2019. In the study, the sustainability performance of insurance companies is assessed by considering three dimensions, which are economic, social and environmental indicators.

Chen and Lu (2015) employed FAHP and fuzzy modified TOPSIS methods to evaluate and compare the performance of four leading insurance companies in Taiwan. Ksenija et al. (2017) evaluated the performance of twenty-eight insurance companies in Serbia based on five financial criteria by employing the FAHP and TOPSIS methods over the period 2007–2014. Torbati and Sayadi (2018) utilized the BWM and fuzzy inference system for the assessment and ranking of fifty-two insurance branches' performance according to thirteen criteria in Iran. Suvvari et al. (2019) analyzed twenty-four Indian life insurance companies' financial performance by taking into account four dimensions such as liquidity, capital adequacy, profitability and activity rates. The study applying the GRA method covers a four-year period between 2013 and 2016. Shen et al. (2017) proposed a hybrid approach to financial performance evaluation of life insurance companies using the DANP and fuzzy integral methods.

2.2 Studies Using the PFAHP Technique

The first component of the proposed two-stage hybrid MCDM model we suggest is the PFAHP approach. Some of the studies employing the PFAHP technique are summarized below. Ilbahar et al. (2018) utilized PFAHP to determine probability and severity parameters in terms of occupational health and safety. Gul (2018) developed an approach for risk assessment via PFAHP and fuzzy VIKOR methods. Gul and Ak (2018) proposed a hybrid approach using the 5×5 risk matrix and the PFAHP and FTOPSIS to assess risk ratings. Ozdemir and Gul (2019) measured the development level of 26 NUTS-2 regions of Turkey by PFAHP and TODIM methods. Büyüközkan and Göçer (2019) assessed digital supply chain partners with AHP and COPRAS methods under Pythagorean fuzzy sets. Karasan et al. (2019) applied PFAHP to the landfill location selection problem. Mete (2019) integrated failure mode and effect analysis, PFAHP and PFMOORA to evaluate occupational risks of a natural gas pipeline construction project. Yucesan and

Kahraman (2019) defined risks in hydroelectric power plants and evaluated risk factors by PFAHP. Shete et al. (2020) identified the supply chain innovation enablers factors for the Indian manufacturing industry by PFAHP. Tepe and Kaya (2020) applied PFAHP and neutrosophic analytic hierarchy process for risk assessment for asphalt production. Çalık (2020) proposed a framework for green supplier selection considering Industry 4.0 components. Öztayşi et al. (2019) prioritized the expectations of different stakeholders to design a social open innovation platform by PFAHP. Wang et al. (2020) conducted a case study in the tropical rainforest of China for ecological landslide prevention with PFAHP. Yucesan and Gul (2020) analyzed hospital service quality by using PFAHP and PFTOPSIS methods. Nguyen et al. (2022) proposed a PFAHP-PFCoCoSo model for benefit expectations in artificial intelligence adoption. Singer and Özşahin (2022) explored the crucial factors influencing wooden outdoor furniture selection by interval-valued PFAHP. Demir et al. (2022) used PFAHP and VIKOR methods in the area of transportation. Lahane and Kant (2023) investigated and specified the importance level of the key challenges of circular supply chain adoption.

2.3 Studies Utilising the MAIRCA Technique

Another component of the hybrid model used in this study is the MAIRCA procedure. Some of the studies using the MAIRCA and its extensions can be summarized as follow. Pamučar et al. (2014) combined fuzzy DEMATEL and MAIRCA for railway level crossing selection. Gigović et al. (2016) utilised a hybrid model based on the combination of geographic information systems and MAIRCA in identifying the best site among nine alternatives for ammunition depots in Serbia. Pamučar et al. (2017) presented a hybrid MCDM model based on interval rough numbers consisting of ANP, DEMATEL, and MAIRCA to determine the most favorable bidder among ten alternatives. Chatterjee et al. (2018) used the R'AMATEL (combining the DEMATEL and ANP methods)-MAIRCA model in evaluating the environmental performance of suppliers for a Taiwanese electronics company Badi and Ballem (2018) proposed a Rough BWM-MAIRCA model for selecting the best medical supplier among three alternatives in Libya. Pamučar et al. (2018) proposed a two-step hybrid MCDM model incorporating fuzzy DEMATEL and MAIRCA to select the location of a multimodal logistics center. Pamučar et al. (2019) suggested a framework by combining the FUCOM and MAIRCA methodologies for the evaluation of level crossings. Zolfani et al. (2020) employed an integrated BWM-MAIRCA methodology for neighborhood selection for a newcomer in Chile. Bakır et al. (2020) combined the PIPRECIA and MAIRCA for the performance evaluation of the airline industry. Boral et al. (2020) suggested a hybrid MCDM model based on the integration of the FAHP and fuzzy MAIRCA for comparison of rankings of eight failure models. Božanić et al. (2020) integrated LBWA and Z-MAIRCA methods for choosing the best location for a camp space among ten alternatives. Gul and Ak (2020) developed a new model combining fuzzy BWM and fuzzy MAIRCA for occupational risk assessment. Ecer and Aycin (2022) applied various ranking strategies, including the MAIRCA method, to assess

the innovation performance of the G-7 countries. Ecer (2022) used an extended MAIRCA procedure based on intuitionistic fuzzy sets to determine the best among five alternative coronavirus vaccines. Narayanamoorthy et al. (2023) developed the linear diophantine hesitant fuzzy sets based MAIRCA procedure to assess sustainable energy storage systems.

3 Research Gaps

In today's competitive environment, insurance companies have to conduct systematic performance measurement to both optimize their business processes and improve their operations. Competitiveness in the insurance market cannot be attributed solely to the efficiency of insurers, as it also depends on insurers' ability to maximize financial and market performance and improve the quality of their services. Although efficiency is often associated with profit performance, it alone is insufficient to provide satisfactory information about firms' profitability, financial strength, and market performance (Bilbao-Terol et al., 2022).

The results of detailed literature review indicate that past studies have mostly focused on analyzing the efficiency or financial performance of unlisted insurers, which suggests that the number of existing studies evaluating listed insurers via decision-making approaches is excessively scarce. This reveals that many earlier studies have neglected the criteria related to market performance while analyzing the overall performance of insurers. Hence, this result reveals that more comprehensive and practical assessment criteria are needed to meet the requirements of decision-makers in the insurance industry.

It has subsequently been found that DEA methodology or its variations are generally applied as a mathematical tool to evaluate the efficiency of insurance companies in terms of selected indicators (inputs and outputs) in most of the studies in the existing literature. However, the DEA has several weaknesses and structural problems. DEA is sensitive to the choice of criteria. If the indicators utilized as inputs and outputs are not carefully chosen, serious deviations in the ranks are likely to occur. Additionally, the number of variables employed can influence the results of analyses of companies' performance and each additional variable can lead to dramatic changes in the ranking results (Forouzandeh et al., 2022; Görçün et al., 2022; Johns et al., 1997). As for techniques such as ANP, AHP, FAHP, BWM, TOPSIS and GRA utilized in the evaluation of the insurance industry, they have some limitations and structural problems like DEA. Due to the rank reversal problem, these methods can be insufficient to produce reliable and consistent results. In other words, adding or deleting an alternative or criterion causes dramatic changes in ranking performance. Besides, ANP, AHP, FAHP and BWM approaches cannot adequately take into account the uncertainties that arise during the evaluation process. These limitations are still debated and criticized in the existing literature (Ak et al., 2022; Görçün et al., 2022; Sánchez-Garrido et al., 2022; Zolfani et al., 2021).

To fill the first important gap mentioned above, the present study introduces a new set of criteria for more effective and realistic analysis of overall performance by

incorporating financial variables, factors affecting service quality and critical market performance indicator into the decision-making process.

To fill the second critical gap, the current paper develops an integrated MCDM approach based on PFAHP and MAIRCA methods to systematically analyze overall performance of listed insurers. Combining the advantages of PFAHP and MAIRCA techniques, this integrated hybrid tool offers a new performance analysis approach as an effective, powerful and applicable mathematical tool in performance analysis of publicly traded insurance companies.

The originality of this study comes from the evaluation of the overall performance of publicly quoted insurers in the Turkish insurance market for the first time. Additionally, this study provides a new and practical set of criteria for performance analysis and evaluation for publicly traded companies in the insurance industry. Finally, there have been no studies utilizing the combination of FPAHP and MAIRCA for the same case in the past.

4 Suggested Hybrid Methodology

In our study an integrated MCDM model including PFAHP and MAIRCA methods is proposed to assess the performance of non-life insurance companies. The first stage involves designing the hierarchy of problems. For this aim, firstly main criteria, sub-criteria, and criteria are determined through reviewing the literature and interviewing three experts in the field. Then, financial indicators of the companies are obtained from the FINNET database and reports of the companies. As a result of the first evaluation, we realized that the indicators determined are not available for every company. For this reason, some companies were excluded. Consequently, five listed companies are included in the structure. The second
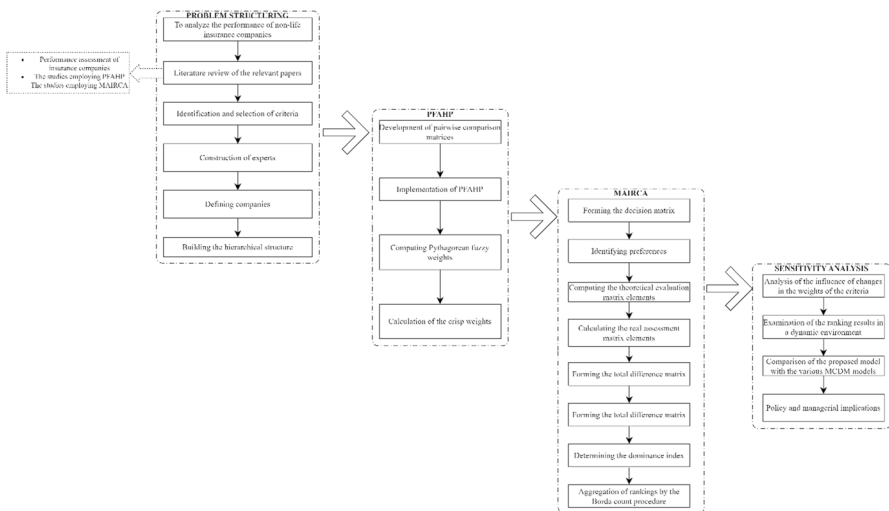

Fig. 1 Outline of the study

stage involves a linguistic evaluation of indicators and acquiring of the weights of indicators based on the PFAHP method (usage of Eqs. 7–13). The last stage involves the ranking of the companies by using the MAIRCA method (usage of Eqs. 14–24). Hence, this section explains the application steps of the two methods mentioned above. Next, a merged ranking for alternatives is provided by employing the five-year performance rankings through the BC rank aggregation technique. Finally, a comprehensive sensitivity analysis is conducted to test the validity of the findings obtained from the integrated PFAHP-MAIRCA framework. Figure 1 outlines the research framework adopted in this study.

4.1 Preliminaries of Pythagorean Fuzzy Sets

In this section, basic concepts and definitions of PFSs are presented. In PFSs, the sum of membership and non-membership degrees can exceed 1, but the sum of squares cannot (Karasan et al., 2018; Zeng et al., 2016; Zhang & Xu, 2014). This situation is shown below in Definition 1.

Definition 1 Let a set X be a universe of discourse. A PFS P is an object having the form (Zhang & Xu, 2014):

$$P = \left\{ < x, P\big(\mu_P(x), v(x)\big) > \mid x \in X \right\} \tag{1}$$

where $\mu_P(x) : X \mapsto [0, 1]$ defines the degree of membership and $v_P(x) : X \mapsto [0, 1]$ defines the degree of non-membership of the element $x \in X$ to P, respectively, and, for every $x \in X$, it holds:

$$0 \leq \mu_P(x)^2 + v_P(x)^2 \leq 1 \tag{2}$$

For any PFS P and $x \in X$, $\pi_P(x) = \sqrt{1 - \mu_P^2(x) - v_P^2(x)}$ is called the degree of indeterminacy of x to P.

Definition 2 Let $\beta_1 = P(\mu_{\beta_1}, v_{\beta_1})$ and $\beta_2 = P(\mu_{\beta_2}, v_{\beta_2})$ be two Pythagorean fuzzy numbers, and $\lambda > 0$, then the operations on these two Pythagorean fuzzy numbers are defined as follows (Zeng et al., 2016; Zhang & Xu, 2014):

$$\beta_1 \oplus \beta_2 = P\left(\sqrt{\mu_{\beta_1}^2 + \mu_{\beta_2}^2 - \mu_{\beta_1}^2 \mu_{\beta_2}^2}, v_{\beta_1} v_{\beta_2} \right) \tag{3}$$

$$\beta_1 \otimes \beta_2 = P\left(\mu_{\beta_1} \mu_{\beta_2}, \sqrt{v_{\beta_1}^2 + v_{\beta_2}^2 - v_{\beta_1}^2 v_{\beta_2}^2} \right) \tag{4}$$

$$\lambda \beta_1 = P\left(\sqrt{1 - \left(1 - \mu_{\beta_1}^2\right)^{\lambda}}, \left(v_{\beta_1}\right)^{\lambda} \right), \lambda > 0 \tag{5}$$

Table 1 Linguistic terms for importance weights of criteria

Linguistic variables	Pythagorean fuzzy numbers			
	μ_L	μ_U	v_L	v_U
Certainly Low Importance—CLI	0.00	0.00	0.90	1.00
Very Low Importance—VLI	0.10	0.20	0.80	0.90
Low Importance—LI	0.20	0.35	0.65	0.80
Below Average Importance—BAI	0.35	0.45	0.55	0.65
Average Importance—AI	0.45	0.55	0.45	0.55
Above Average Importance—AAI	0.55	0.65	0.35	0.45
High Importance—HI	0.65	0.80	0.20	0.35
Very High Importance—VHI	0.80	0.90	0.10	0.20
Certainly High Importance—CHI	0.90	1.00	0.00	0.00
Exactly Equal—EE	0.1965	0.1965	0.1965	0.1965

$$\beta_1^\lambda = P\left(\left(\mu_{\beta_1} \right)^\lambda, \sqrt{1 - \left(1 - v_{\beta_1}^2 \right)^\lambda} \right), \lambda > 0 \tag{6}$$

4.2 Calculation Procedure of the PFAHP Method

The steps of PFAHP are presented as follows.

Step 1: The compromised pairwise comparison matrix $A = \left(a_{ik} \right)_{m \times m}$ is structured based on the linguistic evaluation of experts using the scale proposed by Ilbahar et al. (2018) in Table 1.

Step 2 The difference matrices $D = \left(d_{ik} \right)_{m \times m}$ between the lower and upper values of the membership and non-membership functions are calculated using Eqs. (7) and (8):

$$d_{ik_L} = \mu_{ik_L}^2 - v_{ik_U}^2, \tag{7}$$

$$d_{ik_U} = \mu_{ik_U}^2 - v_{ik_L}^2. \tag{8}$$

Step 3 Interval multiplicative matrix $S = \left(s_{ik} \right)_{m \times m}$ is computed using Eqs. (9) and (10):

$$s_{ik_L} = \sqrt{1000^{d_{ik_L}}}, \tag{9}$$

$$s_{ik_U} = \sqrt{1000^{d_{ik_U}}}. \tag{10}$$

Step 4 The determinacy value $\tau = \left(\tau_{ik} \right)_{m \times m}$ is calculated using Eq. (11):

$$\tau_{ik} = 1 - \left(\mu_{ik_U}^2 - \mu_{ik_L}^2 \right) - \left(v_{ik_U}^2 - v_{ik_L}^2 \right). \tag{11}$$

Step 5 The determinacy degrees are multiplied with $S = \left(s_{ik} \right)_{m \times m}$ matrix for obtaining the matrix of weights, $T = \left(t_{ik} \right)_{m \times m}$ before normalization using Eq. (12).

$$t_{ik} = \left(\frac{s_{ik_L} + s_{ik_U}}{2} \right) \tau_{ik}. \tag{12}$$

Step 6 The priority weights w_i of criteria are normalized by using Eq. (13):

$$w_i = \frac{\sum_{k=1}^{m} t_{ik}}{\sum_{i=1}^{m} \sum_{k=1}^{m} t_{ik}}. \tag{13}$$

4.3 Calculation Procedure of the MAIRCA Method

The MAIRCA method, which is developed in 2014 by the Center for Logistics Research at the University of Defence in Belgrade, is based on the calculation of the gap between theoretical and real ratings in the assessment of alternatives (Pamučar et al., 2014). The following calculation procedure is followed to identify the ranking of the non-life insurance companies (Božanić et al., 2020; Gigović et al., 2016; Zolfani et al., 2020).

Step 1 Forming the decision matrix (A) as shown in the Eq. (14):

$$A = \lceil a_{ij} \rceil_{mxn} = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{m1} & a_{m2} & \cdots & a_{mn} \end{bmatrix} i = 1, 2, \ldots \ldots m; \quad j = 1, 2, \ldots n \tag{14}$$

where, a_{ij} represents the performance value of i-th alternative according to j-th criterion.

Step 2 Identifying preferences (P_{Ai}) according to the selection of alternatives. A decision-maker is neutral in terms of the alternatives during alternative selection and does not have any preferences. All the alternatives are taken into consideration and chosen with equal probability. In other words, the selection possibility for each alternative is equal to each other. For this reason, the process of choosing an alternative from among m alternatives is as follows:

$$P_{Ai} = \frac{1}{m}; \sum_{i=1}^{m} P_{Ai} = 1, i = 1, 2, \ldots, m \tag{15}$$

Here, m is the number of alternatives.

Step 3 Computing the theoretical evaluation matrix elements (T_p). This matrix in a format of mxn is established by multiplying the criteria weights (w_i) obtained from PFAHP method with the preferences P_{Ai} for each alternative as shown in the following equation:

$$T_p = \begin{bmatrix} t_{p11} & t_{p12} & \cdots & t_{p1n} \\ t_{p21} & t_{p22} & \cdots & t_{p2n} \\ \vdots & \vdots & \ddots & \vdots \\ t_{pm1} & t_{pm2} & \cdots & t_{pmn} \end{bmatrix} = \begin{bmatrix} P_{A1}w_1 & P_{A1}w_2 & \cdots & P_{A1}w_n \\ P_{A2}w_1 & P_{A2}w_2 & \cdots & P_{A2}w_n \\ \vdots & \vdots & \ddots & \vdots \\ P_{Am}w_1 & P_{Am}w_2 & \cdots & P_{Am}w_n \end{bmatrix} \tag{16}$$

Step 4 Calculating the real assessment matrix elements (T_r). The real evaluation matrix elements as shown in Eq. (17) are computed as the multiplication of the elements of theoretical evaluation matrix and the normalized elements of the normalized decision matrix.

$$T_r = \begin{bmatrix} t_{r11} & t_{r12} & \cdots & t_{r1n} \\ t_{r21} & t_{r22} & \cdots & t_{r2n} \\ \vdots & \vdots & \ddots & \vdots \\ t_{rm1} & t_{rm2} & \cdots & t_{rmn} \end{bmatrix} \tag{17}$$

The elements in the initial-decision matrix are normalised using Eq. (18) for beneficial criteria, and Eq. (19) for non-beneficial criteria.

$$t_{rij} = t_{pij} \cdot \frac{a_{ij} - a_i^{min}}{a_i^{max} - a_i^{min}} \tag{18}$$

$$t_{rij} = t_{pij} \cdot \frac{a_{ij} - a_i^{max}}{a_i^{min} - a_i^{max}} \tag{19}$$

where a_{ij}, a_i^{max} and a_i^{min} represent the elements of the initial-decision matrix (A) and a_i^{max} and a_i^{min} are maximum and minimum values of the considered criterion, respectively.

Step 5 Forming the total difference matrix (TD). The total difference matrix elements are calculated by subtracting the theoretical assessment matrix elements from the real assessment matrix elements as shown in the following equation:

$$TD = T_p - T_r = \begin{bmatrix} g_{11} & g_{12} & \cdots & g_{1n} \\ g_{21} & g_{22} & \cdots & g_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ g_{m1} & g_{m2} & \cdots & g_{mn} \end{bmatrix} = \begin{bmatrix} t_{p11} - t_{r11} & t_{p12} - t_{r12} & \cdots & t_{p1n} - t_{r1n} \\ t_{p21} - t_{r21} & t_{p22} - t_{r22} & \cdots & t_{p2n} - t_{r2n} \\ \vdots & \vdots & \ddots & \vdots \\ t_{pm1} - t_{rm1} & t_{pm2} - t_{rm2} & \cdots & t_{pmn} - t_{rmn} \end{bmatrix} \tag{20}$$

The difference g_{ij} takes values from the interval $g_{ij} \in [0,\infty]$ by employing Eq. (21):

$$g_{ij} = \begin{cases} 0, & if\, t_{pij} = t_{rij} \\ t_{pij} - t_{rij}, & if\, t_{pij} > t_{rij} \end{cases} \tag{21}$$

Step 6 Obtaining the value of the criteria function (Q_i) and initial ranking of alternatives.

$$Q_i = \sum_{j=1}^{n} g_{ij}, i = 1, 2, \ldots, m \tag{22}$$

The initial evaluation of alternatives is performed based on the obtained values of Q_i and it is decided that the alternative with the lowest Q_i value is the best alternative.

Step 7 Determining the dominance index ($A_{D,1-j}$) of the best-ranked alternative and the final ranking of the alternatives. The dominance index of the best-ranked alternative is computed by employing Eq. (23), and indicates the advantage of the best-ranked alternative in relation to the other alternatives.

$$A_{D,1-j} = \left| \frac{\left| |Q_j| - |Q_1| \right|}{|Q_n|} \right|, j = 2, 3, \ldots, m \tag{23}$$

Where Q_j indicates the value of the criterion function of the alternative in comparison to the best-ranked alternative, Q_1 indicates the criterion function value of the best-ranked alternative, and Q_n indicates the criterion function value of the last-ranked alternative.

After the values of the dominance index are identified, the dominance threshold (I_D) is computed by using Eq. (24)

$$I_D = \frac{m-1}{m^2} \tag{24}$$

Here, m is the number of alternatives.

If the dominance index is greater than or equal to the dominance threshold, the initial ranking will remain unchanged. However, if the dominance index is smaller than the dominance threshold, then it is not possible to say with certainty that the first-ranked alternative has an advantage over the compared alternative and the initial ranking will no longer be valid and the ranking will need to be corrected. For example, if the criterion $A_{D,1-2} < I_D$ is satisfied for the second-ranked alternative, it will be assigned a value of 1* in the ranking. In this case, the best-ranked or second-ranked alternative can be chosen as the first-ranked alternative.

4.4 Borda Count (BC) Procedure

The BC rank aggregation procedure, developed by Jean-Charles de Borda (1781), is a widely applied MCDM aggregation algorithm for obtaining an optimal alternative priority orders with minimum deviations from the originally achieved ranking results of alternatives. The steps of BC are as follows.

Step 1 Identifying the final ranks of options for each different year in a decision problem having *m* options.

Step 2 Assigning points to each option based on the BC method. Considering the Borda rule, the options are assigned scores of (m-1), (m-2), (m-3), etc. starting from the best to the worst. This process is repeated for each year.

Step 3 Obtaining the BC scores for each option. In this step, the sum of the BC scores for each option in each year gives their total BC score.

Step 4 Ranking the options based on their total BC points. The decision options are ranked from highest to lowest, taking into account their total Borda scores. Consequently, the option having the highest BC score is determined as the best option.

5 Application of the Proposed Hybrid Methodology for Non-Life Insurance Companies

The data set used in this study, the hierarchical structure of the problem, and the results of the suggested hybrid model are explained in this section.

5.1 Problem Definition

The performance measurement and assessment to address the challenges to the successful management of insurance corporations is a common problem encountered by various decision-makers in the insurance market (Işık, 2022). To select the best insurer among competitors, it is crucial to consider multiple but often conflicting evaluation criteria. For example, an insurer may perform well when a particular criterion is taken into account, while it may perform poorly in terms of another criterion. The aggregation of these contrasting performances can be provided by employing multi-criteria approaches (Bilbao-Terol et al., 2022).

In this study, a multi-criteria problem concerning the performance measurement and assessment of insurers is given and solved by utilizing a hybrid framework based on PFAHP and MAIRCA methodologies. The determined performance evaluation problem is addressed for five listed non-life insurers and fourteen sub-criteria in three different dimensions.

Given the asset size of financial institutions in the Turkish financial system as of December 2019, insurance companies are the third most important actor in the financial system because they have a 4.71% share in total assets. Moreover, there are a total of 63 companies operating in the Turkish insurance sector. 38 of them are non-life insurance companies. Of the non-life insurance companies, the number of companies whose shares are publicly traded in BIST is 5. These companies are Aksigorta (A1) Anadolu Anonim Türk (A2), Güneş Sigorta (A3) and Halk Sigorta (A4) and Ray Sigorta (A5), respectively. These companies' share in premium production of the non-life insurance market in 2019 is 28,85%.

As seen in Fig. 2, the performance assessment indicators employed in the study consist of fourteen sub-criteria in three dimensions.

- The financial ratios making up the first performance dimension are as follows: (i) the ratio of gross written premiums to equity capital, (ii) the ratio of equity to total assets, (iii) the ratio of current assets to current liabilities, (iv) the ratio of cash plus marketable securities to current liabilities, (v) the ratio of net premiums
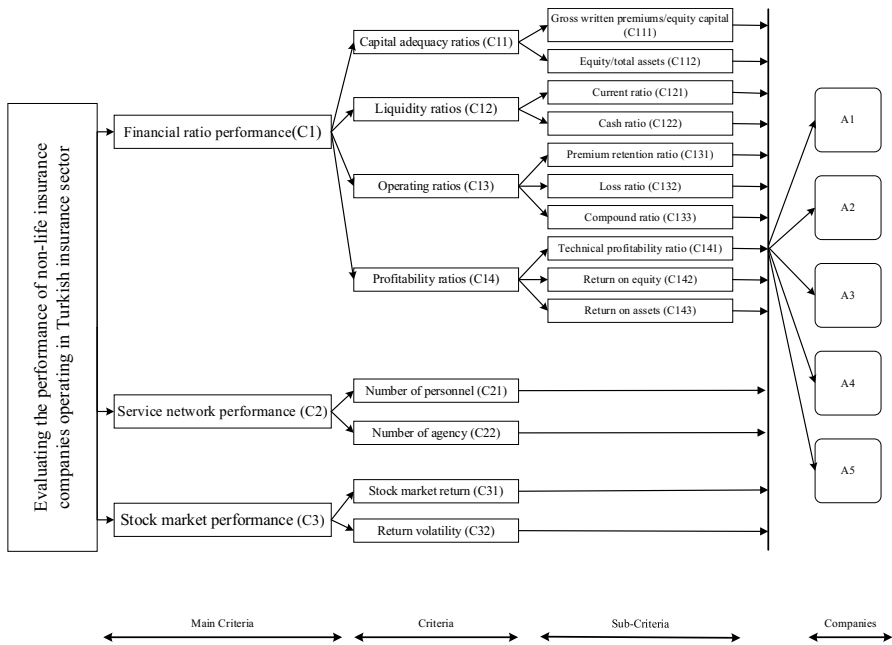
Fig. 2 The hierarchical structure of the problem

to gross premiums, (vi) the ratio of incurred losses to earned premiums, (vii) the ratio of realized claims plus operating expenses to earned premiums, (viii) the ratio of technical profit to gross premiums, (ix) the ratio of net income before taxes to total assets, and (x) the ratio of net income before taxes to stockholder's equity.

- The second performance dimension is related to the service network. This dimension consists of the number of employees and the number of agencies.
- The final performance dimension of the study is based on stock market performance. In this dimension, there are two indicators namely stock return and volatility of stock return (i.e., risk). Stock return (SR) is computed by employing Eq. (25):

$$SR_t = \frac{CP_t - CP_{t-1}}{CP_{t-1}} \times 100 \tag{25}$$

where CP_t and CP_{t-1} are the closing price in year t and $t-1$, respectively.

Stock return volatility is measured as the standard deviation of monthly stock returns for the previous 60 months. The data regarding the financial ratios and service network employed in the study are taken from the annual reports of listed non-life insurers. Whereas, stock market performance data are obtained from the FINNET database. All of the data utilized in this paper are given in Appendix.

Within the framework of the proposed performance evaluation, firstly, assessment criteria are identified through a comprehensive literature review and expert

Table 2 Experts and their detailed information

Experts	Experiences	Graduate	Institute	Position
E1	29	Insurance	University	Prof. Dr
E2	32	Economics	Insurance company	Board Member
E3	21	Business Management	Insurance and Private Pension Regulation and Supervision Agency	President

Table 3 Pairwise comparisons for main criteria

	C1	C2	C3
C1	EE, EE, EE	CLI, HI, VLI	LI, HI, VLI
C2	CHI, LI, VHI	EE, EE, EE	AAI, AAI, AAI
C3	HI, LI, VHI	BAI, BAI, BAI	EE, EE, EE

interviews. Secondly, the data about the insurance companies employed in the analysis are collected. Later, the importance level of the criteria is found using the PFAHP technique in line with the subjective opinions of three experts. Following the calculation of the weight coefficients, the ranking of the companies is provided by the MAIRCA method. Lastly, the ranking results from different years are combined implementing the BC approach to obtain the compromise ranking solution. Figure 2 contains the hierarchical structure of the problem, which consists of five levels: aim, main criteria, criteria, sub-criteria and companies.

5.2 Application of the PFAHP Method

Asking for the opinions of experts having different experiences and knowledge is one of the most crucial steps of the assessment process in structuring and analyzing the decision-making problem. The literature does not provide any information on how many experts should be consulted when applying subjective weighting approaches. However, the number of experts can vary between 2 and 7 in order to achieve reasonable and logical results at the end of the evaluation process (Ecer et al., 2023). For this reason, 5 highly qualified and well-informed experts in the insurance industry were consulted for the purpose of defining and evaluating the performance criteria for listed insurers. However, 3 of them agreed to take part in the evaluation process. Consequently, an expert committee composed of three professionals having more than 21 years of industry experience was established. The detailed information concerning these 3 highly experienced professionals is presented in Table 2.

Next, the criteria of the decision problem are evaluated by these experts. In the first stage, the members of the expert committee constituted pairwise comparisons to identify the level of importance of the criteria. The obtained comparison matrices by expert committee are given in Tables 3 and 4 according to the linguistic scale (Table 1) for the main and sub-criteria, respectively. The aggregated

Table 4 Pairwise comparisons for criteria and sub-criteria

	C11	C12	C13	C14
C11	EE, EE, EE	HI, AAI, BAI	VHI, HI, HI	HI, VHI, LI
C12	LI, BAI, AAI	EE, EE, EE	AAI, AAI, HI	BAI, HI, BAI
C13	VLI, LI, LI	BAI, BAI, LI	EE, EE, EE	LI, AAI, CLI
C14	LI, VLI, HI	AAI, LI, AAI	HI, BAI, CHI	EE, EE, EE

	C21	C22
C21	EE, EE, EE	LI, VLI, HI
C22	HI, VHI, LI	EE, EE, EE

	C31	C32
C31	EE, EE, EE	HI, AAI, BAI
C32	LI, BAI, AAI	EE, EE, EE

	C111	C112
C111	EE, EE, EE	LI, BAI, AAI
C112	HI, AAI, BAI	EE, EE, EE

	C121	C122
C121	EE, EE, EE	VLI, LI, BAI
C122	VHI, HI, AAI	EE, EE, EE

	C131	C132	C133
C131	EE, EE, EE	BAI, LI, AAI	LI, BAI, AAI
C132	AAI, HI, BAI	EE, EE, EE	LI, AAI, AI
C133	HI, AAI, BAI	HI, BAI, AI	EE, EE, EE

	C141	C142	C143
C141	EE, EE, EE	LI, VLI, AAI	AAI, AAI, HI
C142	HI, VHI, BAI	EE, EE, EE	HI, VHI, AAI
C143	BAI, BAI, LI	LI, VLI, BAI	EE, EE, EE

Table 5 Aggregated pairwise comparison matrix for main criteria

	C1	C2	C3
C1	([0.197, 0.197], [0.197, 0.197])	([0.000, 0.000], [0.779, 1000])	([0.254, 0.406], [0.622, 0.762])
C2	([0.516, 0.675], [0.421, 0.557])	([0.197, 0.197], [0.197, 0.197])	([0.550, 0.650], [0.350, 0.450])
C3	([0.453, 0.617], [0.436, 0.586])	([0.350, 0.450], [0.550, 0.650])	([0.197, 0.197], [0.197, 0.197])

Table 6 Weights of criteria

Main Criteria	Weights	Criteria	Weights	Sub-criteria	Weights	Global Weights
C1	0.1711	C11	0.4981	C111	0.3562	0.0304
				C112	0.6438	0.0549
		C12	0.2267	C121	0.1805	0.0070
				C122	0.8195	0.0318
		C13	0.0818	C131	0.2139	0.0030
				C132	0.3536	0.0049
				C133	0.4325	0.0061
		C14	0.1934	C141	0.2675	0.0089
				C142	0.6100	0.0202
				C143	0.1225	0.0041
C2	0.5213	C21	0.3322			0.1732
		C22	0.6678			0.3481
C3	0.3075	C31	0.6438			0.1980
		C32	0.3562			0.1095

pairwise comparison matrix for the main criteria is stated in Table 5. The linguistic evaluations were transformed into the corresponding interval-valued Pythagorean fuzzy numbers and they were combined since the evaluations of the decision makers are different. Finally, the weights of the criteria were obtained by solving the Eq. (7)–(13) steps. The local and global weights of the criteria are presented in Table 6.

From the analytical results shown in Table 6, The service network (C2) is the most important dimension (main criterion) with a weight of 0.5213. Whereas, stock market performance (C3) is the second most important dimension with a weight of 0.3075. Table 5 also states that financial ratios (C1) are the lowest important dimension with a weight of 0.1711.

Table 6 also provides information about the priority weights calculated for the sub criteria. Accordingly, the number of agents (C22) with a weight of 0.3481 is the most important sub-criterion. In addition, stock returns (C31), number of personnel (C21) and return volatility (C32) are other important sub-criteria. On the other hand, the premium retention ratio (C131) is the least important sub-criterion as it has the lowest weight (0.030).

Table 7 The initial decision matrix for the year 2015

	C111	C112	C121	C122	C131	C132	C133	C141	C142	C143	C21	C22	C31	C32
A1	4.6529	0.1855	1.2019	0.8394	68.4949	89.2056	60.7528	− 7.7222	− 31.7400	− 9.1690	678	2270	53.0165	1.9125
A2	3.0042	0.2459	1.1808	0.8337	79.7433	81.5733	56.8034	1.4681	5.6633	2.8702	1083	2561	− 13.1754	1.6625
A3	4.2090	0.1992	0.8380	0.4173	57.9333	98.0000	69.5821	− 11.2214	− 46.9441	− 11.0904	624	1786	− 4.6948	2.2442
A4	4.0858	0.2242	1.3148	1.0107	79.5741	79.7451	47.2166	3.3918	13.5270	1.1528	236	625	14.3455	5.8000
A5	4.7295	0.2087	1.2144	0.7466	50.2033	84.6477	50.8078	− 3.4779	− 14.5475	− 2.7556	246	1254	54.0000	2.5123

5.3 Application of the MAIRCA Method

As mentioned before, the data set covers a 5-years between 2015 and 2019. Therefore, firstly the MAIRCA method is applied to the 2015 data of non-life insurance companies and then the same application procedure is repeated for the remaining four years. The decision matrix formed for the year 2015 by using Eq. (14) is indicated in Table 7.

Following the forming of initial-decision matrix, the preferences are identified as $P_{Ai} = 1/5 = 0.20$, i.e. $P_{A1} = P_{A2} = \ldots = P_{A5} = 0.20$. In the next step, the elements of the T_p matrix as shown in Table 8 are calculated based on Eq. (19). The elements of the T_r are obtained from Eq. (17), and presented in Table 8. Once both the T_p matrix and the T_r matrix are constructed, the TD matrix is calculated through Eq. (20), and given in Table 9. After identifying the total difference (Table 10) between theoretical and actual assessments, to make the first evaluation of the alternatives, the values of Q_i for each alternative is obtained with the help of Eq. (22), and the results are given in Table 11. According to the results, the initially best-ranked alternative is A5.

However, as mentioned above, the value of the dominance index of the best-ranked alternative is computed by applying Eq. (23) to make the final decision as to whether the alternative that ranks first in the performance ranking has enough advantage over other alternatives. Also, the value of the dominance threshold is calculated as 0.16 for our sample with the help of Eq. (24).

Because the dominance index of the best-ranked alternative (A5) in relation to the second-ranked alternative (A4) is smaller than the computed dominance threshold, we can say that A4 does not have enough advantage in relation to A5, thus the ranking for A4 is corrected and A4 takes the value of 1* in the ranking. The other values calculated for the dominance index are greater than the dominance threshold, so the initial ranking remains unchanged for the other alternatives. As a consequence, the order of alternatives for the year 2015 as shown in Table 11 is as follows: A5≈A4 > A1 > A3 > A2.

The results of the proposed performance evaluation model for the remaining four years as well as the year 2015 are indicated in Table 11. As shown in Table 11, the order of A3 and A4 in 2016, the order of A5 in 2018 and the order of A3 in 2019 are corrected due to the reasons mentioned above. Both initial and final ranking results for the year 2017 in Table 11 indicate that alternative A4 is the best-ranked alternative because its advantage is significant enough, compared to the other alternative. As a consequence, the analysis results covering a period of five years reveal that A4 is more dominant than other alternatives, although there is significant competition between A4 and A5.

5.4 Final Ranking of Companies Using BC Method

As mentioned before, our study covers a period of 5 years. Therefore, the rankings of the companies on a yearly basis are determined within the framework of the proposed

Table 8 The theoretical evaluation matrix for the year 2015

	C111	C112	C121	C122	C131	C132	C133	C141	C142	C143	C21	C22	C31	C32
A1	0.0061	0.0110	0.0014	0.0064	0.0006	0.0010	0.0012	0.0018	0.0040	0.0008	0.0346	0.0696	0.0396	0.0219
A2	0.0061	0.0110	0.0014	0.0064	0.0006	0.0010	0.0012	0.0018	0.0040	0.0008	0.0346	0.0696	0.0396	0.0219
A3	0.0061	0.0110	0.0014	0.0064	0.0006	0.0010	0.0012	0.0018	0.0040	0.0008	0.0346	0.0696	0.0396	0.0219
A4	0.0061	0.0110	0.0014	0.0064	0.0006	0.0010	0.0012	0.0018	0.0040	0.0008	0.0346	0.0696	0.0396	0.0219
A5	0.0061	0.0110	0.0014	0.0064	0.0006	0.0010	0.0012	0.0018	0.0040	0.0008	0.0346	0.0696	0.0396	0.0219

Table 9 The real evaluation matrix for the year 2015

	C111	C112	C121	C122	C131	C132	C133	C141	C142	C143	C21	C22	C31	C32
A1	0.0058	0.0000	0.0011	0.0045	0.0004	0.0005	0.0005	0.0004	0.0010	0.0001	0.0166	0.0105	0.0390	0.0206
A2	0.0000	0.0110	0.0010	0.0045	0.0006	0.0009	0.0007	0.0015	0.0035	0.0008	0.0000	0.0000	0.0000	0.0219
A3	0.0042	0.0025	0.0000	0.0000	0.0002	0.0000	0.0000	0.0000	0.0000	0.0000	0.0188	0.0279	0.0050	0.0188
A4	0.0038	0.0070	0.0014	0.0064	0.0006	0.0010	0.0012	0.0018	0.0040	0.0007	0.0346	0.0696	0.0162	0.0000
A5	0.0061	0.0042	0.0011	0.0035	0.0000	0.0007	0.0010	0.0009	0.0022	0.0005	0.0342	0.0470	0.0396	0.0174

Table 10 The total difference matrix for the year 2015

	C111	C112	C121	C122	C131	C132	C133	C141	C142	C143	C21	C22	C31	C32
A1	0.0003	0.0110	0.0003	0.0018	0.0002	0.0005	0.0007	0.0014	0.0030	0.0007	0.0181	0.0592	0.0006	0.0013
A2	0.0061	0.0000	0.0004	0.0019	0.0000	0.0001	0.0005	0.0002	0.0005	0.0000	0.0346	0.0696	0.0396	0.0000
A3	0.0018	0.0085	0.0014	0.0064	0.0004	0.0010	0.0012	0.0018	0.0040	0.0008	0.0159	0.0418	0.0346	0.0031
A4	0.0023	0.0039	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0001	0.0000	0.0000	0.0234	0.0219
A5	0.0000	0.0068	0.0003	0.0028	0.0006	0.0003	0.0002	0.0008	0.0019	0.0003	0.0004	0.0226	0.0000	0.0045

Table 11 Summary of year-wise ranking

		Alternatives				
		A1	A2	A3	A4	A5
2015	Q_i	0.0991	0.1536	0.1227	0.0516	0.0415
	initial rank	3	5	4	2	1
	$A_{D,1-j}$	0.3750	0.7298	0.5283	0.0657	0.0000
	final rank	3	5	4	1*	1
2016	Q_i	0.1289	0.1607	0.0742	0.0767	0.0697
	initial rank	4	5	2	3	1
	$A_{D,1-j}$	0.3683	0.5661	0.0281	0.0438	0.0000
	final rank	4	5	1*	1**	1
2017	Q_i	0.1229	0.1445	0.1072	0.0393	0.0956
	initial rank	4	5	3	1	2
	$A_{D,1-j}$	0.5784	0.7279	0.4699	0.0000	0.3896
	final rank	4	5	3	1	2
2018	Q_i	0.1253	0.1497	0.0913	0.0387	0.0482
	initial rank	4	5	3	1	2
	$A_{D,1-j}$	0.5782	0.7417	0.3511	0.0000	0.0638
	final rank	4	5	3	1	1*
2019	Q_i	0.1411	0.1078	0.0850	0.0657	0.0991
	initial rank	5	4	2	1	3
	$A_{D,1-j}$	0.5342	0.2983	0.1371	0.0000	0.2366
	final rank	5	4	1*	1	3

Table 12 Final rankings of companies based on BC method

	Rank based number					Total	Aggregated rank
	2015	2016	2017	2018	2019		
A1	2	1	1	1	0	5	4
A2	0	0	0	0	1	1	5
A3	1	4	2	2	4	13	3
A4	4	4	4	4	4	20	1
A5	4	4	3	4	2	17	2

methodology. However, it reveals that the final decision regarding the evaluation of companies is not clear. In such cases, the literature suggests various integration methods in order to aggregate the year-wise ranking results and reduce the problem to a single result (Biswas et al., 2022; Ecer, 2021). One of them is the BC method. BC scores calculated for each alternative also provide a consensus ranking between the performance rankings obtained by using five different data. The rankings obtained based on the performance indicators of five different years covering the 2015–2019 period are merged with the Borda rule and the findings are given in Table 12. The final order of alternatives is as follows: A4 > A5 > A3 > A1 > A2.

5.5 Sensitivity Analysis

Verifying the suitability of applying the proposed framework to compare companies with a comprehensive sensitivity analysis is of paramount importance for the stability and reliability of the results obtained. At this point, the stability of the proposed framework is validated through sensitivity analysis in three phases: (i) investigation of the impact of changes in criteria weights on ranking results, (ii) examination of ranking results in a dynamic environment, and (iii) comparison of the proposed hybrid model with the various MCDM approaches. The ranking results found by the application of other MCDM methods are integrated with the BC method.

5.5.1 Analysis of the Influence of Changes in the Weights of the Criteria on the Ranking of Alternatives

Although there are many sensitivity analyses in the MCDM literature regarding weight coefficients, the approach applied by (Božanić et al., 2021; Pamucar et al., 2021) is preferred for this study. By applying this method of conducting sensitivity analysis, the weight of the most important criterion (C22) is reduced by 2% in each scenario. Then, the weights of the remaining 13 criteria are proportionally corrected to meet the sum of weights, which should be equal to 1. In this way, 30 scenarios are formed, as in Table 13. By transferring the new weights found with each scenario to the MAIRCA model, a new ranking of alternatives is obtained. As can be seen in Fig. 3, it is concluded that there is no change in the order of the alternatives obtained by applying the 30 scenarios, which means that the results from sensitivity analysis are substantially stable. Thus, it is verified that the initial rank of the alternatives is not violated.

5.5.2 Examination of the Ranking Results in a Dynamic Environment

In this sub-section, the effects of adding or eliminating a new alternative to the decision matrix on the ranking results are investigated in order to test the robustness and stability of the proposed model for performance assessment (Dwivedi et al., 2023; Nedeljković et al., 2021). In this way, the resistance of the proposed methodology to the rank reversal problem can be tested. In the framework of this study, the performance of the proposed methodology is tested by eliminating the worst alternative from a set of alternatives (Yu et al., 2022; Zolfani et al., 2021). In line with this objective, we generate four scenarios (S1-S4) by removing the worst alternative and observe the changes in the results of ranking. The initial ranking results suggest that the worst alternative is A2. Therefore, in the first scenario, alternative A2 is excluded from the initial decision matrix, while the remaining alternatives are reordered. As can be seen from Table 14, the new ranking result obtained from the first scenario is A4 > A5 > A3 > A1. Similarly, in the next three scenarios, the worst alternatives are removed from the decision matrix and new rankings of alternatives are obtained. The results for all scenarios are reported in Table 14. According to the results reported in Table 14, A4 is ranked first in all scenarios, suggesting that the introduced methodology is considerably consistent and stable and is not influenced by the rank reversal problem.

Table 13 Experimental cases for sensitivity analysis

Cases	C111	C112	C121	C122	C131	C132	C133	C141	C142	C143	C21	C22	C31	C32
S-0	0.0304	0.0549	0.0070	0.0318	0.0030	0.0049	0.0061	0.0089	0.0202	0.0041	0.1732	0.3481	0.1980	0.1095
S-1	0.0309	0.0554	0.0075	0.0323	0.0035	0.0054	0.0066	0.0094	0.0207	0.0046	0.1737	0.3411	0.1985	0.1100
S-2	0.0315	0.0560	0.0081	0.0329	0.0041	0.0060	0.0072	0.0100	0.0213	0.0052	0.1743	0.3343	0.1991	0.1106
S-3	0.0320	0.0565	0.0086	0.0334	0.0046	0.0065	0.0077	0.0105	0.0218	0.0057	0.1748	0.3276	0.1996	0.1111
S-4	0.0325	0.0570	0.0091	0.0339	0.0051	0.0070	0.0082	0.0110	0.0223	0.0062	0.1753	0.3211	0.2001	0.1116
S-5	0.0330	0.0575	0.0096	0.0344	0.0056	0.0075	0.0087	0.0115	0.0228	0.0067	0.1758	0.3147	0.2006	0.1121
S-6	0.0335	0.0580	0.0101	0.0349	0.0061	0.0080	0.0092	0.0120	0.0233	0.0072	0.1763	0.3084	0.2011	0.1126
S-7	0.0339	0.0584	0.0105	0.0353	0.0065	0.0084	0.0096	0.0124	0.0237	0.0076	0.1767	0.3022	0.2015	0.1130
S-8	0.0344	0.0589	0.0110	0.0358	0.0070	0.0089	0.0101	0.0129	0.0242	0.0081	0.1772	0.2962	0.2020	0.1135
S-9	0.0349	0.0594	0.0115	0.0363	0.0075	0.0094	0.0106	0.0134	0.0247	0.0086	0.1777	0.2902	0.2025	0.1140
S-10	0.0353	0.0598	0.0119	0.0367	0.0079	0.0098	0.0110	0.0138	0.0251	0.0090	0.1781	0.2844	0.2029	0.1144
S-11	0.0357	0.0602	0.0123	0.0371	0.0083	0.0102	0.0114	0.0142	0.0255	0.0094	0.1785	0.2787	0.2033	0.1148
S-12	0.0362	0.0607	0.0128	0.0376	0.0088	0.0107	0.0119	0.0147	0.0260	0.0099	0.1790	0.2732	0.2038	0.1153
S-13	0.0366	0.0611	0.0132	0.0380	0.0092	0.0111	0.0123	0.0151	0.0264	0.0103	0.1794	0.2677	0.2042	0.1157
S-14	0.0370	0.0615	0.0136	0.0384	0.0096	0.0115	0.0127	0.0155	0.0268	0.0107	0.1798	0.2623	0.2046	0.1161
S-15	0.0374	0.0619	0.0140	0.0388	0.0100	0.0119	0.0131	0.0159	0.0272	0.0111	0.1802	0.2571	0.2050	0.1165
S-16	0.0378	0.0623	0.0144	0.0392	0.0104	0.0123	0.0135	0.0163	0.0276	0.0115	0.1806	0.2520	0.2054	0.1169
S-17	0.0382	0.0627	0.0148	0.0396	0.0108	0.0127	0.0139	0.0167	0.0280	0.0119	0.1810	0.2469	0.2058	0.1173
S-18	0.0386	0.0631	0.0152	0.0400	0.0112	0.0131	0.0143	0.0171	0.0284	0.0123	0.1814	0.2420	0.2062	0.1177
S-19	0.0389	0.0634	0.0155	0.0403	0.0115	0.0134	0.0146	0.0174	0.0287	0.0126	0.1817	0.2371	0.2065	0.1180
S-20	0.0393	0.0638	0.0159	0.0407	0.0119	0.0138	0.0150	0.0178	0.0291	0.0130	0.1821	0.2324	0.2069	0.1184
S-21	0.0397	0.0642	0.0163	0.0411	0.0123	0.0142	0.0154	0.0182	0.0295	0.0134	0.1825	0.2277	0.2073	0.1188
S-22	0.0400	0.0645	0.0166	0.0414	0.0126	0.0145	0.0157	0.0185	0.0298	0.0137	0.1828	0.2232	0.2076	0.1191
S-23	0.0404	0.0649	0.0170	0.0418	0.0130	0.0149	0.0161	0.0189	0.0302	0.0141	0.1832	0.2187	0.2080	0.1195
S-24	0.0407	0.0652	0.0173	0.0421	0.0133	0.0152	0.0164	0.0192	0.0305	0.0144	0.1835	0.2144	0.2083	0.1198

Table 13 (continued)

Cases	C111	C112	C121	C122	C131	C132	C133	C141	C142	C143	C21	C22	C31	C32
S-25	0.0410	0.0655	0.0176	0.0424	0.0136	0.0155	0.0167	0.0195	0.0308	0.0147	0.1838	0.2101	0.2086	0.1201
S-26	0.0413	0.0658	0.0179	0.0427	0.0139	0.0158	0.0170	0.0198	0.0311	0.0150	0.1841	0.2059	0.2089	0.1204
S-27	0.0417	0.0662	0.0183	0.0431	0.0143	0.0162	0.0174	0.0202	0.0315	0.0154	0.1845	0.2017	0.2093	0.1208
S-28	0.0420	0.0665	0.0186	0.0434	0.0146	0.0165	0.0177	0.0205	0.0318	0.0157	0.1848	0.1977	0.2096	0.1211
S-29	0.0423	0.0668	0.0189	0.0437	0.0149	0.0168	0.0180	0.0208	0.0321	0.0160	0.1851	0.1938	0.2099	0.1214
S-30	0.0426	0.0671	0.0192	0.0440	0.0152	0.0171	0.0183	0.0211	0.0324	0.0163	0.1854	0.1899	0.2102	0.1217

Fig. 3 Result of sensitivity analysis
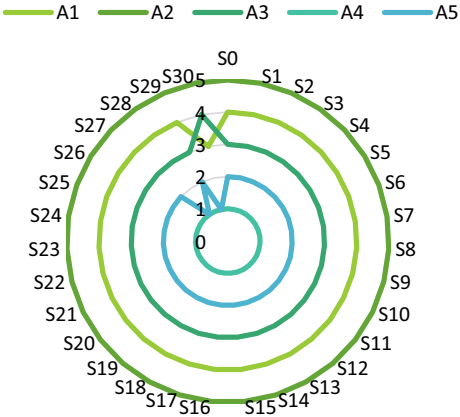
Table 14 The new ranking of the alternatives according to the scenarios

Scenario	Ranks				
Original	A4	A5	A3	A1	A2
S-1	A4	A5	A3	A1	
S-2	A4	A5	A3		
S-3	A4	A5			
S-4	A4				

5.5.3 Comparison of the Proposed Model with the Various MCDM Models

Before drawing any conclusions. it is necessary to perform a validation check to see if the results of the introduced methodology are reliable. Validation refers to comparing the results of several different MCDM methods. In the present study we compare our results with other MCDM approaches such as compromise ranking of alternatives from distance to ideal solution (CRADIS), complex proportional assessment (COPRAS), proximity indexed value (PIV), TOPSIS, and operational competitiveness ratings (OCRA). These procedures are chosen for their various advantages, ease of use, simplicity, wide applications, and potential to efficiently rank alternatives in real-world problems. The methods such as CRADIS (Puška et al., 2022), COPRAS (Kaklauskas & Zavadskas, 1996), PIV (Mufazzal & Muzakkir, 2018), TOPSIS (Hwang & Yoon, 1981), and OCRA (Parkan, 1994) have been proposed for the solution process of various MCDM problems. Among them, the CRADIS and PIV methods are relatively newer compared to the other three methods. The rank of companies obtained by the MAIRCA procedure is compared to the ranks of other MCDM procedures mentioned above. The results for the comparison of the various MADM procedures is demonstrated in Fig. 4. When we examine the comparison results, it has been confirmed that A4 is the best alternative while A2 ranks last in all applied ranking methodologies. The ranking performance of alternatives A5, A3, and A1 is almost identical except for one ranking method. Employing Spearman's rank correlation test, we also check for statistical significance of results from
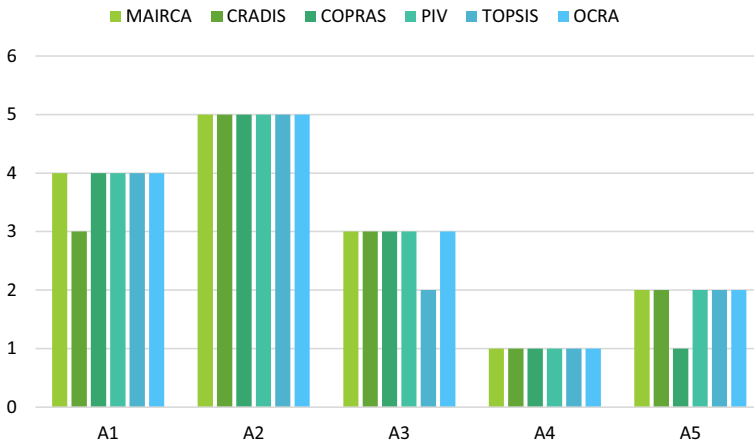
Fig. 4 Comparison of consolidated rankings according to different MCDM methods

Table 15 Spearman's correlation results for different MCDM-based approaches

	MAIRCA	CRADIS	COPRAS	OCRA	PIV	TOPSIS
MAIRCA	1.0000					
CRADIS	0.9747	1.0000				
COPRAS	0.9747	0.9474	1.0000			
OCRA	1.0000	0.9474	0.9747	1.0000		
PIV	1.0000	0.9474	0.9747	1.0000	1.0000	
TOPSIS	0.9747	0.9211	0.9211	0.9747	0.9747	1.0000

all models applied in this study. The results of the rank correlation test for all implemented models are indicated in Table 15. Based on Table 15, it is noticed that correlation values are significantly above 0.92, suggesting a highly significant correlation between the ranks from the tested MCDM procedures and the initial rank from the employed MAIRCA approach. Consequently, validation test results imply that the suggested ranking is validated and can be considered credible.

5.6 Theoretical and Managerial Implications

Insurance firms, which act as a risk transfer mechanism in every economy, take an intermediary role in transferring the funds they collect as premiums for assuming risk from individuals and institutions to financial markets. On the other hand, insurance companies also play an important role in compensating for damages such as natural disasters, fires, and accidents. Thus, it can be stated that insurance services are of great importance not only economically but also socially. Determining the performance of insurance companies facing various challenges and

recommending an evaluation system can be considered a critical issue for practitioners and researchers.

The theoretical implications of our paper can be summarized as follows.

- The introduced PFSHP-MAIRCA framework provides decision support for various DMs, such as managers, policyholders, agents, banks, and supervisory authorities, to make more realistic assessments and analyses by identifying crucial factors influencing the overall performance.
- First, the PFAHP is applied to compute the subjective weight coefficients of the criteria. The PFAHP technique, which is a combination of PFSs with AHP, gives DMs more flexibility in dealing with the complexity of the decision-making environment and enables them to achieve more reliable, consistent, and robust outputs. Second, the MAIRCA approach is responsible for comparing and ranking the performance of non-life insurers. The calculation of a predefined dominance threshold within this algorithm helps DMs to objectively make their final decision on performance evaluation. Additionally, compared to other CRM approaches, it provides DMs with high solution stability even if new alternatives and criteria are added to the decision problem. Hence, more realistic evaluations can be easily made in the insurance market.
- The reliability and applicability of the introduced PFSHP-MAIRCA framework are checked through a three-stage sensitivity analysis. The obtained results demonstrate that the introduced decision framework is an efficient and robust procedure that DMs related to the insurance market can implement without an advanced mathematical background.
- The proposed mathematical tool could be applied by researchers and authorities to analyze the overall performance of financial and non-financial companies in detail and to manage the decision-making process effectively.

The current study has several managerial implications in terms of the results achieved, which can be summarized as follows:

- The proposed methodology can help identify the most important indicator and sub-indicators in the insurance industry.
- Based on the decision-making group judgments and the application of the PFAHP technique, it is deduced from Table 6 that 'service network performance' is preferred as the highest priority among performance categories. For this reason, companies need to pay more attention to the elements that make up their service networks in order to produce better customer-orientated solutions and improve overall performance. Giving the highest priority by decision-makers to factors such as the number of employees and agencies that make up the service network in performance evaluation reveals how important the employees and agencies, whose number has increased rapidly in recent years are in the premium production.

- The average of those with a degree in insurance among university and master's graduates in Turkey is only 5%. Given the findings regarding the service network dimension, increasing this ratio will both solve the problem of qualified personnel in the industry and accelerate the growth of the industry which has a dynamic structure.
- In addition to the above determinations, the increase in digitalization investments for the work of agencies, especially during epidemic periods, may contribute to the development of the service network.
- Considering the stock market performance dimension, it can be stated that the investors in the Turkish insurance industry are more interested in the rate of return rather than the risk.
- The fact that the importance level of the capital adequacy dimension is higher than that of other financial ratios reveals the importance of these ratios for the efficient management of unforeseen risks in insurance, which is built on the concept of risk.
- Considering the performance ranking of the insurers for the five-years, Halk Sigorta is the most successful company. This result reveals the trust of individuals and institutions towards a state-owned insurance company in risk management.
- Top executives associated with insurance firms, including board members can adopt the proposed approach to see their position in the industry in which they operate with a view to achieving and maintaining a sustainable competitive advantage.
- Since monitoring the operating results of insurance companies is of great importance for the national economy and the development of the financial sector, regulatory and supervisory authorities can improve novel and specific strategies for the industry.
- The proposed decision framework can assist potential customers, as well as current policyholders who have already utilized insurance services, to identify the best insurer by comparing insurers in terms of overall performance. It can also contribute to the long-term strategic decision-making of key business partners of the insurance industry, such as agents and banks.
- The paper's findings could provide vital information to other actors in financial markets to effectively manage and improve their financial relationships with insurance companies.
- Finally, our results reveal that the usage of multi-criteria evaluation methods is an important tool in measuring and evaluating the performance achieved by companies from various perspectives in a certain period.

6 Conclusions

Insurance companies are one of the most crucial institutions of the financial system, not only in developed economies but also in developing economies. Due to the risk absorption role of the insurance industry, it is necessary to analyze the performance of companies operating in this industry objectively at regular

intervals. Any problem that can occur in the insurance industry directly affects the intermediation function of insurance companies as well as the overall economy, which can lead to both increased insecurity and unrest in the society and crises in the financial market. Therefore, in this study, it is aimed to introduce a new MCDM framework for performance evaluation of non-life insurance companies based on a multidimensional dataset. In accordance with this purpose, to rank and assess the insurance companies, a combined PFAHP-MAIRCA tool has been employed wherein the BC principle has been applied for gaining an aggregated ranking order considering 5 years covering the period 2015–2019.

In the first stage of the implementation of the proposed methodology, The PFAHP method is applied to data of non-life insurance companies to compute the weight coefficients of the selected performance dimensions and sub-criteria. Findings show that the service network is the most important performance dimension. Moreover, number of agencies and premium retention ratios are found to be the most and least important sub-criteria, respectively.

Once the priority weights of the main-criteria and sub-criteria are determined, non-life insurance companies (alternatives) are ranked employing the MAIRCA method in the second stage of the proposed hybrid model. The findings of MAIRCA approach reveal that, except for 2017, there is no dominant alternative in terms of performance ranking for the other four years, in other words, the performance scores of the alternatives are close to each other. We then applied a ranking strategy based on the BC procedure to gain a better understanding of the performance results and achieve a more meaningful performance ranking. In this framework, year-wise rankings are aggregated by applying the BC procedure. The results of MAIRCA based on BC procedure clearly indicate that Halk Sigorta is the best alternative while Anadolu Anonim Türk ranks last.

The most important limitation of this study is that only the data of five non-life insurance companies whose shares are registered in BIST are used. This limitation is also a shortcoming related to evaluations of other insurance companies operating in the same industry. Another limitation of the study can be related to the period chosen for analysis. But, there was no loss of data for these companies in the period of 2015–2019. Performance evaluation studies to be carried out for the insurance sector can be a guide for managers, shareholders, and regulatory and supervisory authorities. Therefore, more insurance companies can be examined within the scope of analysis in future studies. Additionally, nonlinear modeling approaches which proved to be successful in modeling systems in various fields can be used in performance assessment. Finally, it should be noted that including different types of performance dimensions in the analysis process is important for a more effective performance evaluation.

Appendix

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14
2015 Decision Matrix														
A1	4.6529	0.1855	1.2019	0.8394	68.4949	89.2056	60.7528	-7.7222	-31.7400	-9.1690	678.0000	2270.0000	53.0165	1.9125
A2	3.0042	0.2459	1.1808	0.8337	79.7433	81.5733	56.8034	1.4681	5.6633	2.8702	1083.0000	2561.0000	-13.1754	1.6625
A3	4.2090	0.1992	0.8380	0.4173	57.9333	98.0000	69.5821	-11.2214	-46.9441	-11.0904	624.0000	1786.0000	-4.6948	2.2442
A4	4.0858	0.2242	1.3148	1.0107	79.5741	79.7451	47.2166	3.3918	13.5270	1.1528	236.0000	625.0000	14.3455	5.8000
A5	4.7295	0.2087	1.2144	0.7466	50.2033	84.6477	50.8078	-3.4779	-14.5475	-2.7556	246.0000	1254.0000	54.0000	2.5123
2016 Decision Matrix														
A1	3.8380	0.2469	1.3400	0.9367	62.5667	67.0946	38.4534	2.9463	13.5673	7.0728	604.0000	2366.0000	-23.1481	1.7739
A2	3.6659	0.2047	1.1616	0.8591	80.2425	80.1133	55.2696	1.6179	7.2466	3.5139	1163.0000	2556.0000	-12.8342	1.3926
A3	2.7487	0.2872	0.9738	0.5528	56.4659	82.0000	51.2618	-2.9342	-11.9330	1.5508	610.0000	1546.0000	104.2807	2.0830
A4	4.9981	0.1756	1.2196	0.9796	83.6947	81.6841	54.1894	2.1932	11.2096	-1.1982	244.0000	583.0000	-17.0992	5.3619
A5	3.9360	0.2470	1.3360	0.9172	48.9609	68.0807	41.8475	7.2159	31.3270	9.4543	244.0000	1215.0000	-1.9608	2.4278
2017 Decision Matrix														
A1	4.1894	0.2319	1.3102	0.9333	60.9829	65.6877	38.4385	5.3889	22.6157	8.1233	621.0000	2403.0000	-32.0755	1.7888
A2	2.8501	0.2331	1.1767	0.8822	72.4025	81.6717	57.8903	2.8324	12.8710	6.2643	1200.0000	2314.0000	-36.0128	1.2096
A3	2.4513	0.3126	0.9943	0.5974	55.1527	82.0000	53.5473	1.3561	4.5015	1.6782	603.0000	1554.0000	-30.6569	2.2088
A4	6.1103	0.1455	1.1758	0.9912	71.7261	85.4092	60.2616	2.4851	15.7293	-0.9154	240.0000	533.0000	22.0485	3.2044
A5	3.8189	0.2515	1.2857	0.8696	43.7649	79.3511	51.8969	3.2229	12.9185	3.6368	244.0000	1214.0000	-69.0909	2.5836
2018 Decision Matrix														
A1	4.7598	0.2043	1.2628	0.9345	61.4986	73.5016	48.6500	7.3099	33.7949	10.7659	739.0000	2654.0000	-20.3889	1.7080
A2	3.4633	0.2083	1.1827	0.8435	69.1105	86.7363	62.6137	4.1185	18.7247	8.8061	1260.0000	2319.0000	-37.2250	1.0173
A3	2.3775	0.3073	1.0066	0.6233	54.3804	88.0000	58.9161	0.4550	1.4692	1.3484	610.0000	1418.0000	-13.2911	2.4581

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14
A4	4.6822	0.1613	1.1970	0.9560	70.6637	95.1603	72.2958	3.6547	23.6251	-1.1146	244.0000	659.0000	6.8625	3.5940
A5	4.2710	0.2290	1.2630	0.7965	48.7120	79.2510	49.0924	3.4165	14.2995	2.5733	261.0000	1138.0000	6.4516	2.8391
2019 Decision Matrix														
A1	4.9780	0.1950	1.2500	0.9481	61.1930	69.5652	44.6134	9.0205	45.3238	13.0568	664.0000	2878.0000	-43.2297	1.7160
A2	3.0654	0.2207	1.2122	0.8923	70.5396	84.2795	59.0987	4.5618	21.2054	9.7371	1317.0000	2298.0000	-4.5004	0.9732
A3	1.7561	0.3522	1.1789	0.7910	57.3667	78.0000	48.5986	3.9390	11.8101	6.7440	620.0000	1412.0000	-23.0752	2.7027
A4	3.4939	0.1990	1.2485	1.0538	69.5966	95.0870	64.9578	8.6040	47.0997	11.4965	257.0000	860.0000	-33.1423	3.4720
A5	4.7227	0.2054	1.2339	0.7614	46.3809	69.2874	33.8717	4.5474	21.1176	6.1587	282.0000	1303.0000	-45.4225	3.2566

Declarations

Conflict of interest The authors declare that they have no conflict of interest.

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