Abstract

The role of a claims adjuster is to examine an accident and the damage that took place to ensure the customer of the related insurance company, subject to the damage receives sufficient compensation for the claim she filed. While claims adjusters' contributions on the customer satisfaction and the insurance company profitability is high, studies focusing on measuring performance levels of them and highlighting a fair and robust evaluation system with a scientific background is scarce in the literature. This study presents a novel approach by using a modified version of a well-known multicriteria decision-making method, TOPSIS, for the evaluation and ranking of claims adjusters in the context of the auto industry, based on two distinct aspects of evaluation. The first aspect serves the aim of a systematic auto adjuster recruitment process by forming an overall evaluation and scores table in the long-term period. The second aspect of the presented method serves to an assignment problem of adjusters to the claim files according to their demonstrated performances with similar accidents in a daily use case scenario. The whole procedure and verification of the study are based on statistical observations illustrated in a sponsored insurance company example.

Keywords: MCDM, TOPSIS, Claims Adjusters, Ranking, Clustering, Performance Evaluation

Introduction

In Turkey, more than one million traffic accidents have occurred annually for last 10 years (TURKSTAT, 2020). Being traffic insurance for vehicles in traffic is mandatory in Turkey (Turkish Highway Traffic Law, 1983), significant amounts of payments are made by insurance companies each year.

Thus, billions of Turkish Liras are paid by the insurance companies to their customers to compensate their damage amount for accidents. After the accident occurs, process of handling an accident file starts with the report from the policyholder and ends with the payment or denial of payment for damages covered (Viaena et al., 2007). Investigation for the accident is made with the help of an on-site worker named claims adjuster of each company (Viaena et. al., 2007). "Adjusters are responsible for managing claim costs, providing claimants with high-quality customer service and facilitating recovery from the traffic injuries" (Moodley, 2020). Moodley (2020) also mentions decision-making role of a claims adjuster predominantly in assessing the size and cost of the damage. In Turkey's insurance system, claims adjusters are the only authority for the decision of payment to the policyholder (Turkish Insurance Adjusters Regulation, 2008). Under these circumstances, working with the best adjusters and assigning the most convenient one to an accident file in a short time are challenges for insurance companies. In the light of this information, we have collaborated one of the biggest insurance companies in Turkey as the decision-maker and worked with the real accident and claims adjuster data.

In this context, we are dealing with two major problems for insurance companies. First is the selection of adjusters to work together in the long term which means the recruitment of the adjusters to the company. Considering adjusters' growing population in the country and having a limited budget, the complexity and difficulty of the process of making an optimal selection adjuster vastly increase for an insurance company. Second is the assignment of an adjuster who can make fair and accurate decisions for the compensation of the damage in a short time to an accident file. To achieve this goal, the company must assign an adjuster that will probably perform a relatively better job on the file for all stakeholders where being successful can be predefined based on some criteria. Observing all, a strong need for an evaluation system for adjusters is realized by the insurance companies.

This study proposes a new hybrid performance evaluation methodology to close the gap in the evaluation and ranking system in the auto insurance industry for auto claims adjusters, which requires to calculate a desirability function (Derringer and Suich, 1980) and uses a revised version of multicriteria decision-making tool, TOPSIS at the end which is serving to two mentioned challenges by setting two methodological systems for performance evaluation in this project. "The TOPSIS method is flexible and may be used to model a wide variety of decision problems" (Silva et al.,2020). For the assignment of the auto adjusters to the accident files, we designed a system that evaluates the auto adjusters based on the historical accident file data which are grouped in the related cluster where all accident files have similar inherent characteristics with the accident to be assigned. The inherent characteristics which are used as criteria to create differently specified clusters are obtained by the incorporation with the sponsoring company which provided the related historical data about the accident files and the adjusters. As a result of statistical procedures on the provided data, criteria for the clustering process are obtained. And, for the recruitment aspect of auto adjusters, an overall score is calculated for each auto adjuster including all historical accident files.

Yadav et al. (2019) developed a python-based TOPSIS software named as PyTOPS. Being inspired by PyTOPS, we have also introduced a python-based performance evaluation software using the Desirability Function (Derringer and Suich, 1980) to have a scaled score data from all different clusters and to take the criteria directions into the calculation. In the end, TOPSIS is used to evaluate, score, and rank the auto adjusters based on criteria selected among provided options. All criteria included in the score calculations are obtained by discussions made with stakeholders of the project and then, narrowed down to a meaningful final decision. For the calculation of scores of each auto adjuster, the weighted contribution of each criterion is found by using the analytic hierarchy process (AHP) proposed by Saaty (1977, 1980,1986), which also uses the conducted surveys filled out by stakeholders of the project in this study.

In this paper, we described the applied framework and related studies in six sections. In section 1, an introduction to the study and circumstances behind the problem are explained. Section 2 is on the literature research of MCDM methods and other performance evaluation studies. Section 3 introduces the methodology used with the beginning of notation explanation used in the mathematical formulation representations. Section 4 presents a proposed framework for evaluating adjusters with the details of the procedure used in the evaluation. In the fifth section, the primarily specified approaches are studied whether they are satisfied by the verification procedure including a sample from the used historical data. Finally, the procedure and the results of the study are included in the conclusion section. Additionally, the interface of the constructed software is designed to meet the specific needs of the company concerted in the project and the software is kept on the project's Github repository.

Related Work

The studies in the literature about ranking the adjusters in the insurance industry are exceedingly scarce. Since adjusters' performance evaluation can be built upon with some industry-wide criteria, a Multi-Criteria Decision-Making (MCDM) method is a natural choice to calculate performance scores of adjusters and rank them. The objective of using multicriteria decision making is to compare the alternatives that affect the opinion of the decision-maker while considering many criteria, and the issue of sorting the alternatives should be considered thoroughly (Zopounidis & Doumpos, 2001). Different multicriteria decision-making methods have been developed so far applying to different areas such as finance, marketing, energy management, and the environment (Zopounidis & Doumpos, 2002). MCDM methods addressing sorting problems are developed to solve decision-making problems (Silva et. al, 2020).

The simple additive method or weighted sum model (Fishburn, 1967) is probably the most used. The goal Programming method was introduced in Charnes, Cooper & Ferguson (1995). PROMETHEE (Brans, 1982) is used in various areas in various fields. ELECTRE (Roy, 1968) family is introduced to overcome the problems faced while using a weighted sum technique. FINTECH (Zopounidis & Dumpos, 2001), AHP-SORT (Ishizaka, Pearman, & Nemery, 2012), MACHBETHSort (Ishizaka & Gordon, 2017), Fuzzy Goal Programming (Tiwari, Dharmar & Rao, 1987) methods were proposed to solve problems in this nature with different approaches. TOPSIS (technique for order of preference by similarity to ideal solution) is another well-known solution approach for MCDM sorting studies. TOPSIS is first proposed in Hwang & Yoon (1981) and further developments, such as in Yoon (1987) and Hwang, Lai & Liu (1993), followed. Within the project, the main criteria are simplicity, the ability to have a full ranking and ease to use with stable functions in case of adding new accident data in the following years. After all research, TOPSIS Method is considered for the context of the project. The TOPSIS method is a very well-known tool that is used to support multicriteria decision-making (Dwivedi, Srivastava, & Srivastava, 2018; Ferreira et al., 2018; Sabokbar et al., 2016). The basic idea behind the method is to choose the alternative closest to an ideal solution. It is a helpful tool in terms of simplicity, rationality, computationally effectiveness, and the possibility for visualization (Roszkowzka, 2011).

There also exists former uses of TOPSIS method to construct a ranking. The study conducted by Dağdeviren, Yavuz and Kılınç in 2009, utilizes TOPSIS and AHP in a fuzzy environment to rank and select weapons in defense industry. Aydogan (2011) has developed a performance measurement model for aviation firms with rough-AHP and TOPSIS methods under fuzzy environment. In 2011, Lotfi, Fallahnejad and Navidi proposed a ranking method to rank efficient units in DEA via TOPSIS method. In Şengül et. al (2015), an approach of fuzzy TOPSIS is used to rank renewable energy supply systems in Turkey. In Beikkhakhian, et. al (2015), an application of ISM model with fuzzy TOPSIS-AHP methods to evaluate and rank agile suppliers is proposed. Krohling, Pacheco (2015) utilizes a TOPSIS-based approach for ranking evolutionary algorithms.

The method proposed in this article differentiates from its predecessors with application of clustering, application of classification and usage of desirability functions.

Methodology

This section includes the representation of the hybrid performance evaluation methodology designed in two ways related to two different aspects of the adjuster evaluation procedure. The methodology is also proposed step by step in Fig. 1. The main components of the methodology are clustering, classification, desirability functions, percentile rank, and TOPSIS method respectively.

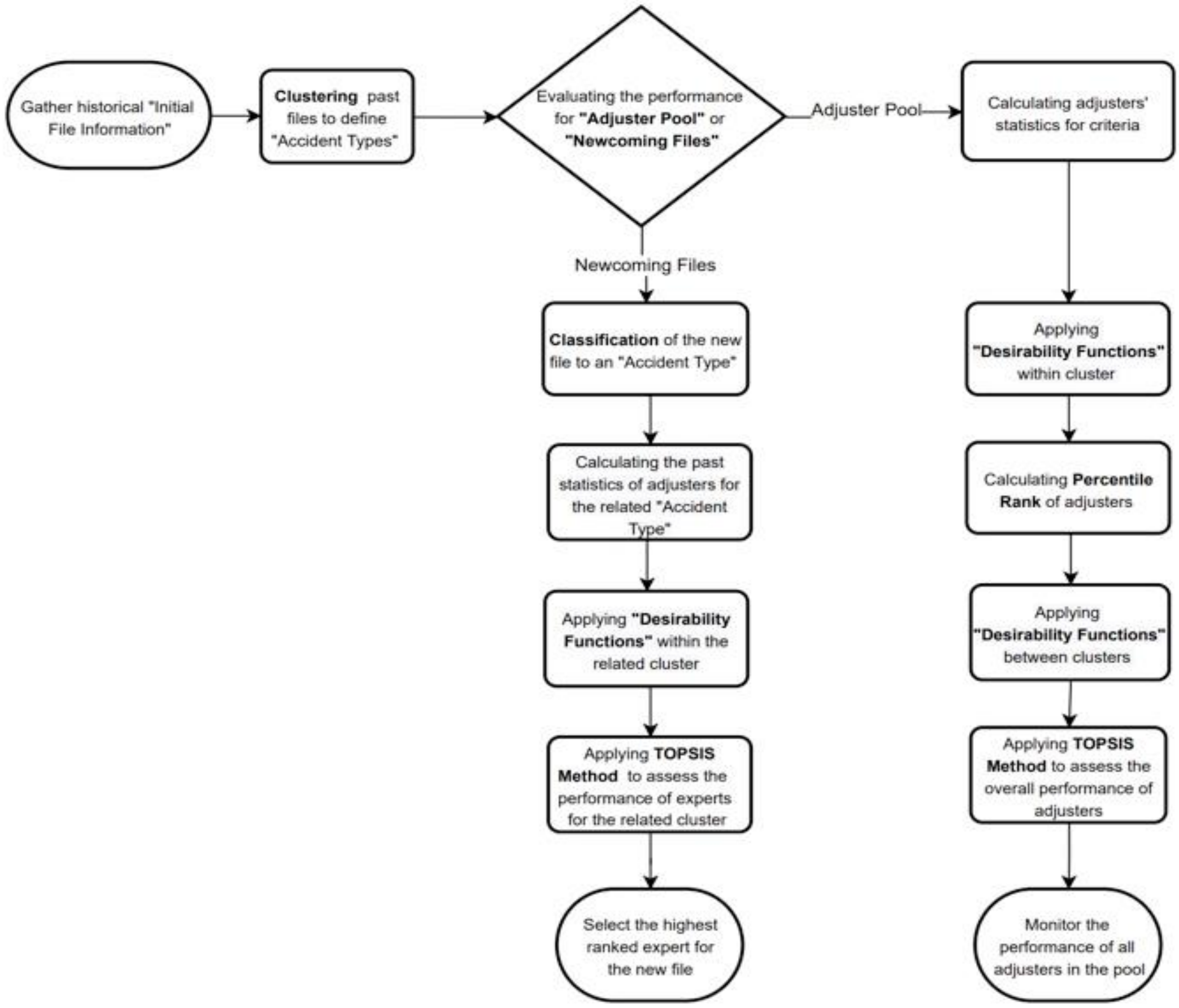

Fig. 1. Flowchart of the proposed methodology

The performance of an adjuster can be evaluated more fairly and comprehensively by considering different intrinsic aspects of files they investigated. Each new accident file can be differentiated according to their initial file information, where initial file information is the information received from the technical service about the accident when the file is opened but the adjuster has not yet investigated the file. Hence, the first step of the methodology is clustering (Jin & Han, 2011) the past files based on initial file information to define clusters. From this point on, "cluster" and "accident type" terms will be used interchangeably.

Notations used at the first step are as follows:

- $A = \{a_1, a_2, a_3, \dots, a_m\}$ be a set of m files
- $F = \{f_1, f_2, f_3, \dots, f_p\}$ be a set of p features for clustering
- $C = \{c_1, c_2, c_3, \dots, c_k\}$ be a set of k clusters

After determining the relevant clustering attributes, k clusters are formed with an appropriate clustering method and c_j becomes accident type j that induces similar accidents to gather under an accident type.

From now on, steps of the methodology will proceed in two branches that are shown in Fig. 1. In the following step, one of two performance evaluation paths should be selected. This decision is made according to the chosen current goal of the performance evaluation. First path considers an overall performance evaluation of adjusters by considering all investigated files in all accident types, which is represented with *"Adjuster Pool"* path. The second path, *"Newcoming Accident"* is selected to assign an auto-adjuster to a file by finding the accident type and taking relevant auto adjusters, which have already accident files in that accident type, into consideration. Here, the threshold value for the number of accidents was determined as a hyperparameter value that can show that a certain adjuster is active or not in an accident type and can be tuned by decision maker.

The second component of the methodology is the classification (Hastie, Tibshirani, & Friedman, 2021) of a new accident file to an accident type. To do so, features of files for clustering are defined as predictors, and accident types are defined as target labels. Then, the dataset is divided into training and validation set to construct the classifier for the new accident. As it is mentioned, features of the clustering, F, are composed of the initial information of the accident. Thus, features of a new accident are used to classify the accident. Auto adjusters are to be evaluated if he/she has any past accident files in the classified accident type -cluster- of the new file. This is the first step for the insurance company in case of having a new accident file and classification is only used for the new accident selection in Fig. 1.

Since different accident types mean different vehicle types, brands, or cities, before gathering performances in one group, we need a similar scale for each cluster. Therefore, the next component is to apply desirability transformation to adjusters' statistics. Also, to create a bridge between clusters by scaling, desirability transformation allows considering mean and standard deviation together. It helps to promote not only the adjusters with better mean values but also the consistent ones.

Some notations used in the rest of the component as follows:

- E = $\{e_1, e_2, e_3, \dots, e_r\}$ be a set of r adjusters
- $e_{r,j,k}^{avg}$ and $e_{r,j,k}^{std}$ are the mean and standard deviation of adjuster e_r regarding criterion g_j in cluster c_k

Let the dummy values $\{a_{j,k}^{+}, a_{j,k}^{-}\}$ and $\{s_{j,k}^{+}, s_{j,k}^{-}\}$ represent domains of $e_{r,j,k}^{avg}$ and $e_{r,j,k}^{std}$, where;

- $a_{j,k}^{+}$, $a_{j,k}^{-}$ are respectively the maximum and minimum values of adjusters for cluster c_k regarding criterion g_j
- $s_{j,k}^{+}$, $s_{j,k}^{-}$ are respectively the maximum and minimum standard deviation of adjusters for cluster c_k regarding criterion g_j
- $T_{j,k}^{avg}$ and $T_{j,k}^{std}$ be the target of mean and standard deviation value regarding criterion g_j in cluster c_k
- $U_{j,k}^{avg}$ and $U_{j,k}^{std}$ be the upper bound of mean and standard deviation value regarding criterion g_j in cluster c_k
- $L_{j,k}^{avg}$ and $L_{j,k}^{std}$ be the lower bound of mean and standard deviation value regarding criterion g_j in cluster c_k
- $d_{r,j,k}^{avg}$ and $d_{r,j,k}^{std}$ be the desirability of adjuster e_r's the mean value and standard deviation regarding criterion g_j in cluster c_k

$$d_{r,j,k}^{avg} = \begin{cases} 0 & if \quad e_{r,j,k}^{avg} < L_{j,k}^{avg} \\ \left(\dfrac{e_{r,j,k}^{avg} - L_{j,k}^{avg}}{T_{j,k}^{avg} - L_{j,k}^{avg}}\right)^{s*} & if \quad L_{j,k}^{avg} \leq e_{r,j,k}^{avg} \leq T_{j,k}^{avg} \\ 1 & if \quad e_{r,j,k}^{avg} > T_{j,k}^{avg} \end{cases} \quad , g_j \in G^{+}$$

$$d_{r,j,k}^{avg} = \begin{cases} 0 & if \quad e_{r,j,k}^{avg} < L_{j,k}^{avg} \\ \left(\dfrac{e_{r,j,k}^{avg} - L_{j,k}^{avg}}{T_{j,k}^{avg} - L_{j,k}^{avg}}\right)^{s*} & if \quad L_{j,k}^{avg} \leq e_{r,j,k}^{avg} \leq T_{j,k}^{avg} \\ 1 & if \quad e_{r,j,k}^{avg} > T_{j,k}^{avg} \end{cases} \quad , g_j \in G^{+}$$

$$d_{r,j,k}^{std} = \begin{cases} 0 & if \quad e_{r,j,k}^{std} > U_{j,k}^{std} \\ \left(\dfrac{e_{r,j,k}^{std} - U_{j,k}^{std}}{T_{j,k}^{std} - U_{j,k}^{std}}\right)^{s*} & if \quad T_{j,k}^{std} \leq e_{r,j,k}^{std} \leq U_{j,k}^{std} \\ 1 & if \quad e_{r,j,k}^{std} < T_{j,k}^{std} \end{cases}$$

The value of s* used in the transformation would be specified by the user. A large value of s* would be specified if it were very desirable for the value of $e_{r,j,k}^{avg}$, for example, to increase rapidly above $L_{j,k}^{avg}$ if $g_j \in G^{+}$(Derringer, and Suich, 1980).

As a final step of applying desirability transformation, overall desirability is calculated as follows:

$$D_{r,j,k} = \left(d_{r,j,k}^{avg}\right)^{w_{avg}} * \left(d_{r,j,k}^{std}\right)^{w_{std}}$$

$$w_{avg} + w_{std} = 1$$

In the next step, the percentile rank of adjusters is calculated. Let $p_{r,j,k}$ be the percentile rank of adjuster e_r regarding criterion g_j in cluster c_k. For example, an adjuster that was ranked in the 10th percentile is considered more successful than 90% of the adjusters in the related cluster for the related criterion.

$t_{r,k}$ be the number of files of adjuster e_r in cluster c_k and $P_{r,j}^{avg}$ be the weighted mean of percentile ranks of adjuster e_r regarding criterion g_j

$$P_{r,j}^{avg} = \sum_k \frac{t_{r,k} * p_{r,j,k}}{\sum_k t_{r,k}}$$

$P_{r,j}^{std}$ be the weighted standard deviation of percentile ranks of adjuster e_r regarding criterion g_j

$$P_{r,j}^{std} = \sqrt{\sum_k \frac{t_{r,k} * \left(P_{r,j}^{avg} - p_{r,j,k}\right)^2}{\sum_k t_{r,k}}}$$

After these steps, like in the previous component, overall desirability of weighted average and weighted standard deviation of percentile ranks of adjuster e_r regarding criterion g_j will be calculated.

Let the dummy values $\{a_j^{P+}, a_j^{P-}\}$ and $\{a_j^{S+}, a_j^{S-}\}$ represent domains of $P_{r,j}^{avg}$ and $P_{r,j}^{std}$, where a_j^{Pavg+}, a_j^{Pavg-} are respectively the maximum and minimum desirability values of adjuster's averages regarding criterion g_j and a_j^{Pstd+}, a_j^{Pstd-} are respectively the maximum and minimum desirability values of adjuster's standard deviations regarding criterion g_j

$D_{r,j}^{Pavg}$ be the desirability of the weighted average of percentile ranks of adjuster e_r regarding criterion g_j

$$D_{r,j}^{Pavg} = \begin{cases} \dfrac{P_{r,j}^{avg} - a_j^{Pavg-}}{a_j^{Pavg+} - a_j^{Pavg-}} \end{cases}$$

$D_{r,j}^{Pstd}$ be the desirability of the weighted standard deviation of percentile ranks of adjuster e_r regarding criterion g_j

$$D_{r,j}^{Pstd} = \begin{cases} \dfrac{P_{r,j}^{std} - a_j^{Pstd+}}{a_j^{Pstd-} - a_j^{Pstd+}} \end{cases}$$

$D_{r,j}^{*}$ be the overall desirability of adjuster e_r regarding criterion g_j

$$D_{r,j}^{*} = \left(D_{r,j}^{Pavg}\right)^{w_{avg}} * \left(D_{r,j}^{Pstd}\right)^{w_{std}}$$

$$w_{avg} + w_{std} = 1$$

In the last component of the methodology, TOPSIS Method is applied to the overall desirability values, $D_{r,j}^{*}$, of adjuster e_r regarding criterion g_j to evaluate and score the performance of the adjuster by regarding all criteria (g_1, g_2, g_3 and g_4). For a better understanding of the TOPSIS Method, let us introduce the notation used at this component. Let E = $\{e_1, e_2, e_3, \dots, e_r\}$ be a set of *r* adjusters who are alternative solutions for this study. Let G = $\{g_1, g_2, g_3, \dots, g_n\}$ be a set of *n* criteria for performance evaluation. Let $D_{r,j}^{*}$ be the overall desirability of adjuster e_r regarding criterion g_j. Let $G^{+}$and G^{-} be respectively the subsets of beneficial and cost criteria. Let W = $\{w_1, w_2, w_3, \dots, w_m\}$ be a vector of weights where w_j is the weight of criterion g_j. The decision matrix, which is constructed right after the calculation of overall desirability, $D_{r,j}^{*}$, is assessed with r adjusters and n criteria are given as follows:

$$\begin{bmatrix} D_{1,1}^{*} & D_{1,2}^{*} & D_{1,3}^{*} & \dots & \dots & \dots & D_{1,n}^{*} \\ D_{2,1}^{*} & D_{2,2}^{*} & \dots & \dots & \dots & \dots & \dots \\ D_{3,1}^{*} & \vdots & D_{3,3}^{*} & \dots & \dots & \dots & \dots \\ \vdots & \vdots & \vdots & \ddots & \dots & \dots & \dots \\ \vdots & \vdots & \vdots & \vdots & \ddots & \dots & \dots \\ \vdots & \vdots & \vdots & \vdots & \vdots & \ddots & \dots \\ D_{r,1}^{*} & \vdots & \vdots & \vdots & \vdots & \vdots & D_{r,n}^{*} \end{bmatrix}$$

After the derivation of the decision matrix, as it is represented, steps of the TOPSIS method is applied to the decision matrix. Steps of the traditional TOPSIS method for ranking are given in Algorithm 1 (Silva et al., 2020). Afterward, a customized version of the TOPSIS method is presented. In this version of the TOPSIS method, absolute deviation in weights, which is formulated in the previous section, and simulation runs are added to the traditional TOPSIS method, which is represented in Algorithm 1. Yadav et al. (2019) have also conducted a TOPSIS study with the parameters like “Degree of Variation in Weights” and “Number of Simulation”.

Algorithm 1 TOPSIS Algorithm

Step 1: Normalize the decision matrix X = $[D^*_{i,j}]_{\text{r x n}}$ and construct the normalized decision matrix Y=$[y_{i,j}]_{\text{r x n}}$ by calculating

$y_{i,j} = (D^*_{i,j}) / \sqrt{\sum_{i=1}^{r} \left(D^*_{i,j}\right)^2}$

Step 2: Construct weighted normalized decision matrix $V = [v_{i,j}$ $_{\text{r x n}}$ by calculating $v_{i,j} = w_j * y_{i,j}$ where $\sum_{j=1}^{n} w_j = 1$

Step 3: Determine the ideal and negative ideal solutions as

$v^+ = [v_1^+, v_2^+, v_3^+, \ldots, v_n^+]$, $\quad v_j^+ = \begin{cases} max_i, v_{i,j}, g_{j \in G^+} \\ min_i, v_{i,j}, g_{j \in G^-} \end{cases}$

$v^- = [v_1^-, v_2^-, v_3^-, \ldots, v_n^-]$, $\quad v_j^- = \begin{cases} min_i, v_{i,j}, g_{j \in G^+} \\ max_i, v_{i,j}, g_{j \in G^-} \end{cases}$

Where v^+ is ideal and v^- is the negative ideal solution.

Step 4: Calculate the separation measure. Separation measure is Euclidean distance of each alternative, e_i, to the ideal and negative ideal solution.

$$d_i^+ = \sqrt{\sum_{j=1}^{n} \left(v_{i,j} - v_j^+\right)^2} \quad \forall_{i=1,2,\ldots,r}$$

$$d_i^- = \sqrt{\sum_{j=1}^{n} \left(v_{i,j} - v_j^-\right)^2} \quad \forall_{i=1,2,\ldots,r}$$

Step 5: Calculate the relative closeness to the ideal solution by

$C(e_i) = \frac{d_i^-}{d_i^+ + d_i^-}, i = 1,2, \ldots, r$

Step 6: Rank the preference order of alternatives in descending order of the closeness coefficient $C(e_i)$.

Step 2 in the customized version is given below.

Customized Step 2: Recalculate weights of criterion considering absolute deviation of them by taking a random value from the following probability distribution;

$r.v\ w_j^{new} \sim U(w_j - abs_j, w_j + abs_j)$

where abs_j means the absolute deviation of the creation j and w_j^{new} is the new value of the weight of the criterion j.

To have $\sum_{j=1}^{n} w_j^{new} = 1$, the following routine is applied to all weights of criteria to normalize them.

$w_j^{new} = \frac{w_j^{new}}{\sum_{j=1}^{n} w_j^{new}}\ \forall_j$

Then, w_j equals to the w_j^{new} and construct weighted normalized decision matrix $V = [v_{i,j}$ r x n by calculating $v_{i,j} = w_j * y_{i.j}$ where $\sum_{j=1}^{n} w_j = 1$

Another contribution to the traditional TOPSIS method is making simulations with varied weights drawn from a uniform distribution defined at Step 2. This contribution is necessary due to the randomness in selecting weights from a uniform distribution. The customized version of Step 6 and the additional step, Step 7, are given below.

Customized Step 6: Using closeness coefficient, $C(e_i)$, calculate the TOPSIS score of each adjuster in every simulation run, $ts_{sn}(e_i)$, ranging from 0, for the adjuster having the worst performance in all criteria, to 100, for the adjuster having the best performance in all criteria, where *sn* is the intended number of simulation runs and $ts_{sn}(e_i)$ *represents the TOPSIS score of adjuster i in sn*th *simulation run. (*Yadav et al., 2019*)*

Then, go back to Step 1 until *sn* reaches the intended simulation number to generate randomness.

Step 7 (Additional to the Algorithm 1): Calculate the mean value of the TOPSIS scores in each simulation run for every adjuster by

$ts(e_i) = \frac{\sum_1^{sn} ts_{sn}}{sn}\ \forall_i$. Then, rank the preference order of alternatives, adjusters, in descending order of the mean TOPSIS score.

Other steps remain the same in the customized version of the TOPSIS method, which is implemented through this study, as it has been represented in Algorithm 1. This component, the steps above, is implemented as the last step in both configurations named “Adjuster Pool” and “New Accident File” as it is seen in Fig. 1.

The proposed framework for evaluating adjusters

The decision problem discussed in this research involves the ranking of a group of auto insurance adjusters both in one type of accident as in daily use or as a long-term evaluation with all accident types, following the needs of the insurance company. Fig. 2 presents the proposed applied framework for this application, including TOPSIS and Desirability functions.

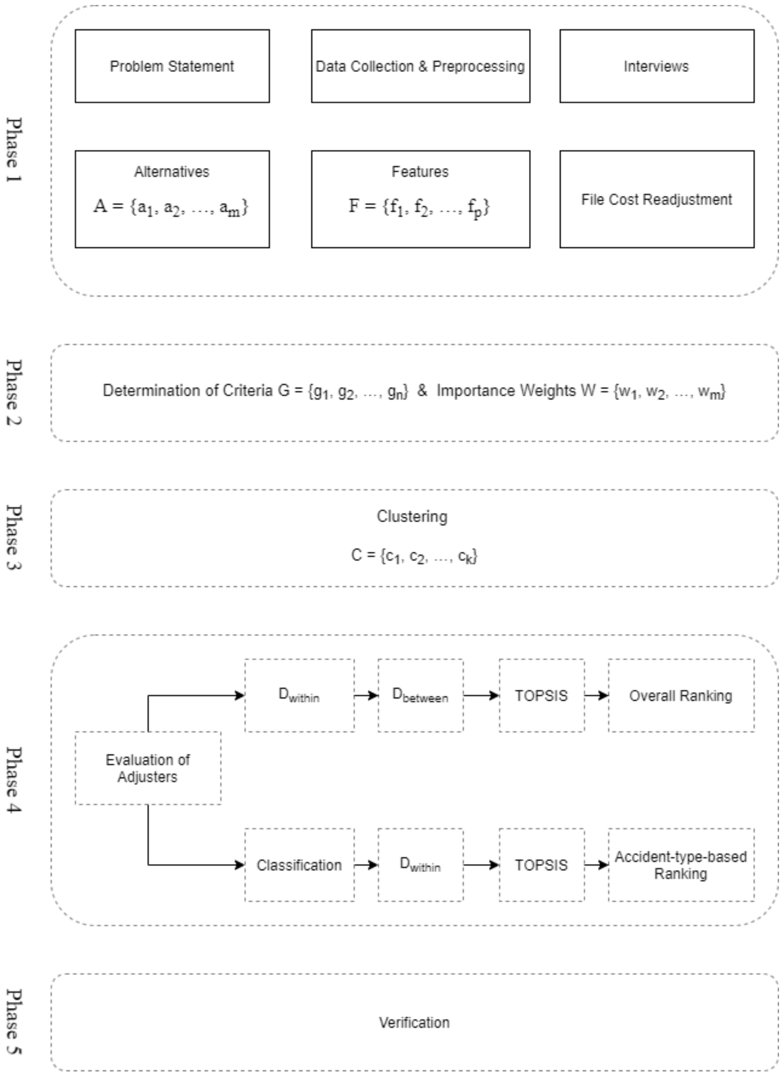

Fig. 2. The proposed applied framework for evaluating adjusters based on Desirability functions & TOPSIS

5.1 Collection of Data

In Phase 1, data of the accident files examined by adjusters between 2017 and 2019 were obtained from the company's database. Files with a file closure time of over 60 days or a total file closing cost under 50 ₺ or above 200000 ₺ were considered as outliers by the decision-maker and excluded from data. Also, as a ratio widely used as a rule of thumb to describe accidents in the auto insurance industry, the total file closing costs of all files were readjusted by proportioning the value of the relevant vehicles collected from Vehicle Value List (Turkey Insurance Union, 2019). For vehicles that do not have an exact match in the Value List, a string-matching procedure was carried out using the longest common substring similarity (Zhang et al., 2017) method to the closest vehicle model's value.

5.2 Determining Criteria & Importance Weights

In Phase 2, after conducting the interviews with the decision-maker, the prominent criteria for an adjuster's evaluation process were determined. In the second phase, a survey was conducted with the five company employees. Their importance weights are determined by a flexible AHP spreadsheet template tool (Goepel, 2013), resulting in a reasonably acceptable consistency index of 0.16. The results are shown in Table 1.

Table 1
Prominent criteria for adjuster evaluation

	Criterion	Description	Direction	Weights
g_1	Customer Satisfaction	The satisfaction rate of a customer from an adjuster	Max	0.278
g_2	Percentage of Disclaim	Voluntarily withdrawal of a customer from her file's inspection	Max	0.254
g_3	Percentage of Declines	Refusal of an adjuster to be assigned to a file	Min	0.218
g_4	Technical Service Satisfaction	The satisfaction rate of technical service from an adjuster	Max	0.111
g_5	File Closure Time	Repair time of a vehicle	Min	0.077
g_6	File Closure Cost / Vehicle Value	Capital needed to repair a vehicle divided by vehicle value	Min	0.062

5.2 Clustering

Traffic accidents with varying characteristics and severity occur for different reasons due to the dynamic conditions of the real world. Kadilar (2014) developed a conditional logistic regression model to identify factors affecting the severity of accidents in Turkey and found that factors such as the driver's age, road conditions, road type, accident time, and accident location were statistically significant. (Eboli et al., 2020) leveraged various machine learning techniques to determine the severity of accidents that occurred in Italy and demonstrated that road stretch type and signposting affect the outcome substantially. As accidents can be a result of many factors grow out of the natural complexity of the real world, there is a lack of consensus to formally identify and categorize accident types by some predefined parameters. Hence, there is also a lack of consensus in the definition of similarity of accidents. In this research, the concept of accident types and similar accidents were defined by looking through the lens of the insurance company with the use of relevant data in an unsupervised manner. In the data, before any adjuster is assigned to an accident file, the initial accident information that can be used in similar accident identification is presented in Table 2.

Table 2
Initial accident information

Feature	**Feature Type**	**Dimension**
Vehicle Type	Discrete	11
Brand	Discrete	117
Model	Discrete	13483
Model Year	Discrete	55
Insurance Type	Discrete	2
Service Type	Discrete	2
City	Discrete	81
District	Discrete	563
Estimated Damage Cost (₺)	Continuous	-

In Phase 3, to reduce the complexity of rapidly growing dimensions in the feature space while forming accident types, a specific part of the discrete features was transformed into continuous features, as in Table 3. Here, an assumption was taken that these discrete features’ intrinsic properties can be captured by continuous features. The Socio-Economic Index (Dincer et al., 2003) stated in Table 3 is a development indicator that reflects the social and economic nature of Turkish cities as a continuous variable. Finally, the damage level feature was decided to be formed due to the non-negligible probability of two accidents' damage severities can be different even when all other factors are the same or similar. The damage level feature is constructed from vehicle value and estimated initial damage cost where this cost is based on preliminary estimates of the technical service before the adjuster is assigned to the file.

Table 3
Features for clustering

	Feature	Created By
f_1	Vehicle Value	Vehicle Type, Brand, Model, Model Year
f_2	Socio-Economic Index	City, District
f_3	Damage Level	Vehicle Value, Initial Estimated Damage Cost
f_4	Insurance Type	-
f_5	Service Type	-

Clustering was performed with the CLARA method (Hadi et al., 1992), which considers the inherent nature of categorical data, and accident types were created.
In the evaluation of clustering, Silhouette and Elbow (Yuan & Yang, 2019) methods were used to calculate the optimal number of clusters. The Silhouette method supported the existence of a high number of clusters, while the Elbow method suggested fewer (see Fig. 3 and Fig. 4). To solve this conflict, inspired by (Ren & Fan, 2011), Algorithm 1 is used to select the optimal number of clusters, $k_{optimal}$, as 170 (see Fig. 5).

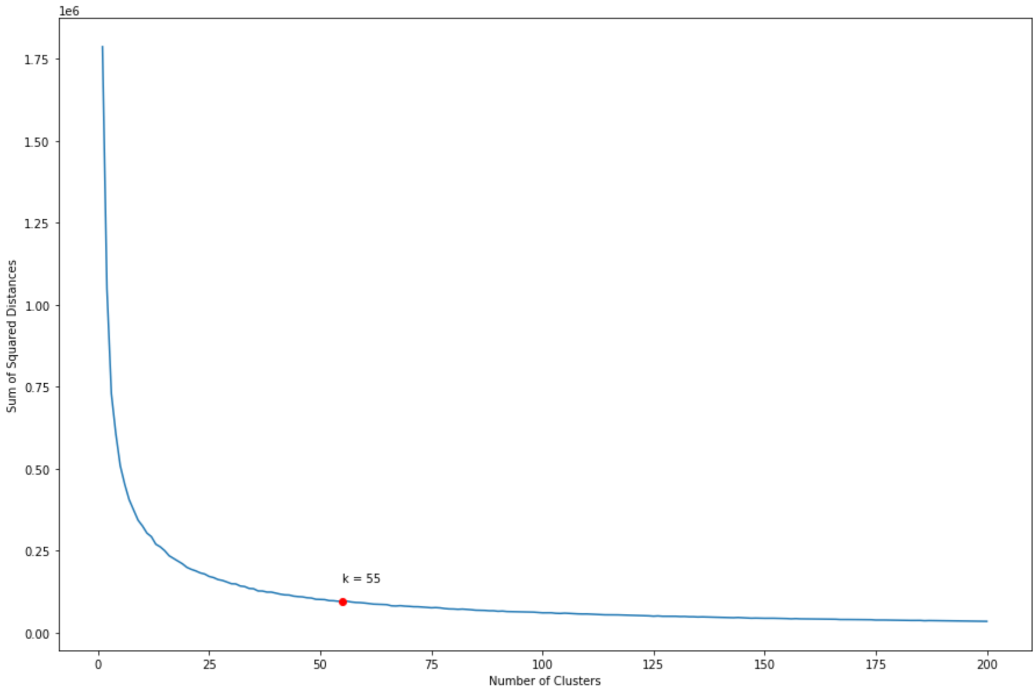

Fig. 3. Elbow Method Plot

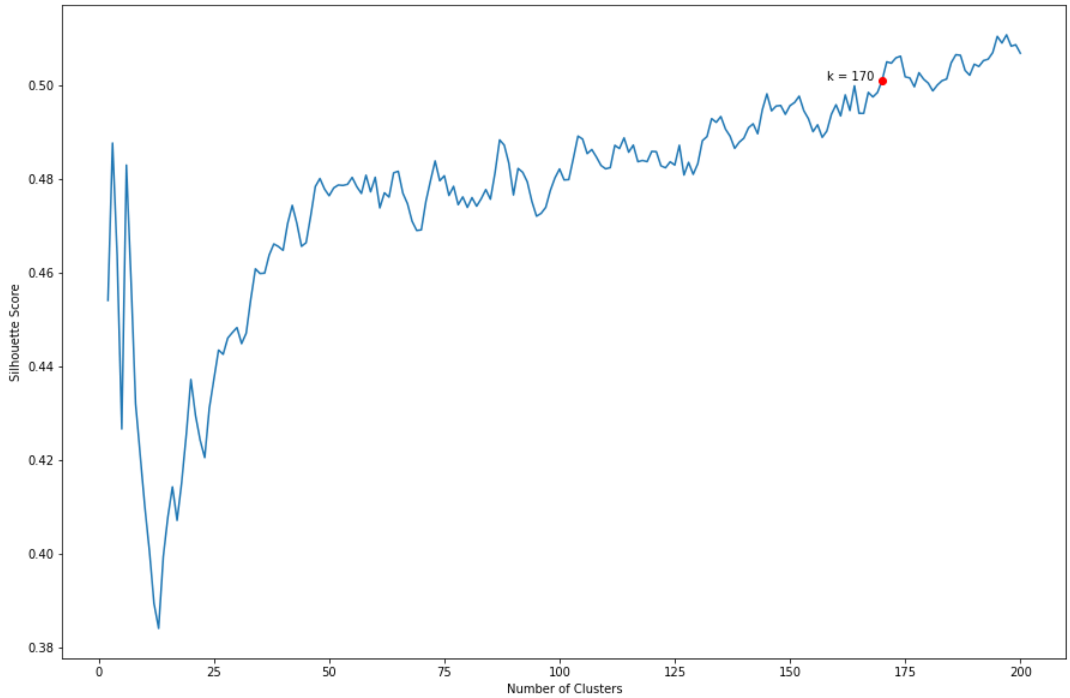

Fig. 4. Silhouette Score Plot

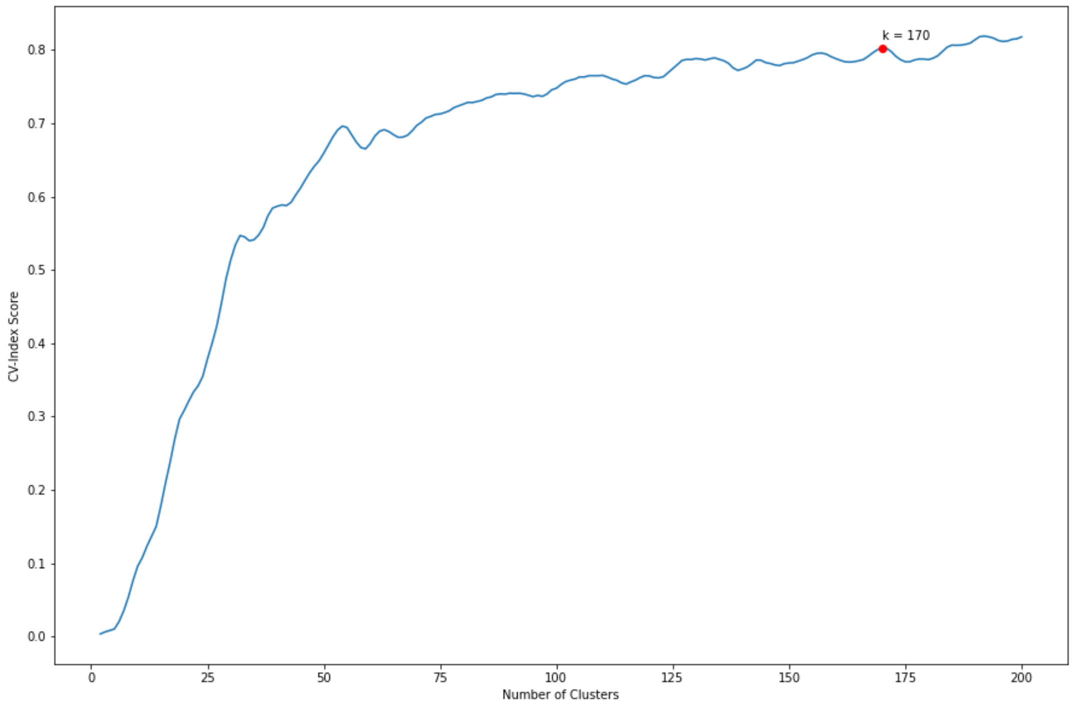

Fig. 5. CV-Index Score Plot

Algorithm 2 Cluster Validation Index routine.

Step 1: Initialize the number of clusters $k = 1$

Step 2: Increment the value of k by 1

Step 3: Apply the CLARA method and obtain clusters C = $\{c_1, c_2, c_3, \ldots, c_k\}$ for files A = $\{a_1, a_2, a_3, \ldots, a_m\}$ with features F = $\{f_1, f_2, f_3, \ldots, f_p\}$

Step 4: Calculate the coefficient of variation (CV) for cluster i as $CV(c_i)$ and for feature j as $CV(f_j)$, $\forall c_i \in C,\ f_j \in F$

Step 5: If $CV(c_i) \leq 0.25$ and $CV(f_j) \leq 0.25,\ \forall c_i \in C,\ f_j \in F,$ go to Step 6. Otherwise, go back to Step 2.

Step 6: Accept $k_{optimal} = k$

5.3 Desirability Functions and TOPSIS

In Phase 4, adjusters are evaluated in two scenarios following the needs of the company. In the overall ranking scenario, all adjusters affiliated with the company are periodically evaluated in the long term, and the company's adjuster pool is updated by excluding the worst-performing adjusters from the pool. In the adjuster assignment scenario, a new file currently open is assigned to the best performing and available adjuster according to its accident type.

5.3.1 Overall Adjuster Evaluation

TOPSIS and Desirability functions described in the methodology section are applied to create the overall ranking of the adjusters. As a result of interviews with the decision-maker, $w_{avg} = 0.8$ and $w_{std} = 0.2$ are used. Due to the lack of customer and service satisfaction data, g_1 and g_4 are not included in the overall ranking of adjusters. Response types for the rest of the criteria are shown in Table 4. The decision matrix for the TOPSIS method is introduced in Table 5. The truncated results obtained by applying the approach described in Algorithm 2 are presented in Table 6.

Table 4
Response type for each criterion value

Criterion	**Value**	**Response Type**
g_2	Mean	Larger-the-better
g_3	Mean	Smaller-the-better
g_5	Mean	Smaller-the-better
g_6	Mean	Smaller-the-better
g_2	Standard Deviation	Larger-the-better
g_3	Standard Deviation	Smaller-the-better
g_5	Standard Deviation	Smaller-the-better

g_6	Standard Deviation	Smaller-the-better

Table 5

Decision Matrix for Global Ranking of Adjusters

Alter / Criterion	g_2	g_3	g_5	g_6
e_{199}	0.003	0.069	0.027	0.046
e_{263}	0.068	0.070	0.022	0.071
e_{51}	0.002	0.068	0.064	0.037
e_{136}	0.081	0.020	0.004	0.067
e_{103}	0.004	0.069	0.048	0.057
e_{171}	0.003	0.070	0.048	0.060
e_{172}	0.003	0.051	0.013	0.066
e_{146}	0.084	0.066	0.024	0.043
e_{125}	0.067	0.038	0.017	0.027
e_{117}	0.066	0.070	0.022	0.043
e_{236}	0.084	0.002	0.030	0.067
e_{149}	0.079	0.016	0.027	0.055
e_{197}	0.082	0.069	0.030	0.068
e_{20}	0.085	0.044	0.032	0.064
e_{152}	0.069	0.029	0.036	0.040
e_{170}	0.062	0.069	0.035	0.053
e_{148}	0.071	0.019	0.054	0.067
e_{126}	0.003	0.007	0.035	0.061
e_{169}	0.048	0.035	0.049	0.025
e_{212}	0.085	0.069	0.043	0.060
e_{7}	0.060	0.062	0.059	0.053
e_{19}	0.077	0.066	0.051	0.055
e_{140}	0.080	0.069	0.047	0.061
e_{164}	0.071	0.053	0.063	0.000
e_{232}	0.085	0.069	0.059	0.029
e_{229}	0.060	0.064	0.059	0.071
e_{163}	0.054	0.039	0.059	0.053
e_{128}	0.077	0.059	0.061	0.062
e_{119}	0.077	0.063	0.059	0.047
e_{216}	0.003	0.026	0.054	0.054
e_{11}	0.081	0.060	0.069	0.060
e_{18}	0.003	0.070	0.058	0.030
e_{36}	0.084	0.030	0.064	0.051
e_{32}	0.070	0.069	0.062	0.046
e_{138}	0.084	0.023	0.064	0.069
e_{13}	0.075	0.069	0.063	0.058
e_{118}	0.003	0.049	0.067	0.023
e_{139}	0.083	0.056	0.064	0.049
e_{196}	0.067	0.069	0.064	0.066
e_{230}	0.083	0.011	0.064	0.063
e_{12}	0.068	0.068	0.067	0.062
e_{35}	0.002	0.069	0.067	0.024
e_{129}	0.076	0.070	0.069	0.065
e_{173}	0.075	0.032	0.065	0.050
e_{179}	0.003	0.061	0.071	0.047
e_{30}	0.002	0.058	0.067	0.063
e_{31}	0.084	0.070	0.070	0.049
e_{150}	0.078	0.060	0.072	0.057
e_{246}	0.053	0.070	0.069	0.068
e_{21}	0.057	0.046	0.070	0.046
e_{267}	0.003	0.070	0.071	0.052
e_{215}	0.080	0.070	0.066	0.064
e_{120}	0.002	0.071	0.067	0.072
e_{274}	0.085	0.070	0.070	0.025
e_{289}	0.002	0.039	0.063	0.014
e_{127}	0.002	0.071	0.000	0.048
e_{298}	0.002	0.086	0.101	0.055
e_{10}	0.051	0.060	0.056	0.066
e_{9}	0.008	0.049	0.050	0.041
e_{279}	0.084	0.012	0.054	0.063
e_{55}	0.081	0.068	0.003	0.045
e_{90}	0.082	0.067	0.009	0.060
e_{143}	0.076	0.020	0.020	0.059
e_{54}	0.001	0.008	0.025	0.048
e_{213}	0.080	0.052	0.044	0.068
e_{101}	0.085	0.058	0.016	0.041
e_{168}	0.079	0.068	0.031	0.049
e_{285}	0.002	0.067	0.039	0.070
e_{53}	0.076	0.048	0.045	0.055
e_{83}	0.082	0.059	0.036	0.050
e_{8}	0.071	0.068	0.028	0.039
e_{88}	0.083	0.066	0.031	0.053
e_{176}	0.059	0.061	0.039	0.044
e_{39}	0.077	0.044	0.028	0.062
e_{82}	0.081	0.069	0.041	0.062

e_{81}	0.073	0.046	0.028	0.066	e_{96}	0.082	0.030	0.071	0.038
e_{124}	0.003	0.065	0.034	0.063	e_{265}	0.085	0.070	0.071	0.066
e_{142}	0.060	0.062	0.058	0.053	e_{44}	0.083	0.046	0.041	0.028
e_{154}	0.080	0.069	0.036	0.060	e_{166}	0.001	0.047	0.064	0.061
e_{23}	0.070	0.026	0.040	0.047	e_{106}	0.001	0.056	0.038	0.023
e_{256}	0.063	0.069	0.052	0.040	e_{181}	0.080	0.067	0.047	0.059
e_{245}	0.084	0.067	0.065	0.059	e_{300}	0.001	0.068	0.064	0.072
e_{45}	0.003	0.067	0.037	0.036	e_{292}	0.002	0.027	0.069	0.070
e_{104}	0.083	0.069	0.048	0.066	e_{260}	0.079	0.069	0.039	0.062
e_{276}	0.084	0.050	0.052	0.050	e_{249}	0.044	0.054	0.060	0.065
e_{16}	0.000	0.006	0.062	0.043	e_{177}	0.001	0.015	0.067	0.052
e_{237}	0.073	0.049	0.054	0.043	e_{50}	0.072	0.067	0.046	0.043
e_{218}	0.084	0.023	0.042	0.070	e_{102}	0.079	0.033	0.072	0.069
e_{264}	0.085	0.070	0.059	0.045	e_{180}	0.002	0.034	0.059	0.050
e_{85}	0.001	0.041	0.064	0.045	e_{290}	0.001	0.069	0.070	0.055
e_{29}	0.068	0.065	0.060	0.042	e_{25}	0.067	0.068	0.044	0.042
e_{239}	0.076	0.025	0.052	0.055	e_{303}	0.001	0.071	0.075	0.076
e_{286}	0.002	0.067	0.066	0.064	e_{238}	0.002	0.069	0.070	0.068
e_{52}	0.002	0.064	0.045	0.055	e_{281}	0.004	0.063	0.069	0.029
e_{42}	0.001	0.031	0.053	0.067	e_{65}	0.086	0.061	0.053	0.067
e_{222}	0.002	0.067	0.050	0.070	e_{71}	0.085	0.000	0.026	0.061
e_{24}	0.073	0.064	0.054	0.029	e_{220}	0.076	0.048	0.061	0.051
e_{153}	0.003	0.068	0.051	0.027	e_{158}	0.059	0.053	0.043	0.051
e_{284}	0.063	0.066	0.059	0.054	e_{67}	0.071	0.069	0.054	0.056
e_{43}	0.000	0.068	0.057	0.049	e_{3}	0.059	0.058	0.054	0.064
e_{86}	0.000	0.069	0.057	0.022	e_{26}	0.066	0.064	0.044	0.064
e_{87}	0.083	0.067	0.058	0.065	e_{69}	0.006	0.032	0.054	0.024
e_{221}	0.076	0.003	0.058	0.068	e_{174}	0.007	0.048	0.042	0.044
e_{62}	0.000	0.070	0.058	0.061	e_{160}	0.004	0.069	0.055	0.043
e_{144}	0.084	0.068	0.066	0.062	e_{17}	0.083	0.066	0.066	0.071
e_{58}	0.083	0.053	0.055	0.066	e_{22}	0.063	0.068	0.066	0.013
e_{64}	0.062	0.017	0.066	0.064	e_{4}	0.007	0.012	0.063	0.049
e_{79}	0.000	0.061	0.049	0.054	e_{5}	0.071	0.065	0.066	0.064
e_{41}	0.075	0.014	0.065	0.040	e_{2}	0.067	0.072	0.072	0.038
e_{165}	0.078	0.010	0.059	0.055	e_{273}	0.004	0.014	0.032	0.069
e_{59}	0.070	0.036	0.066	0.050	e_{28}	0.084	0.015	0.069	0.032
e_{226}	0.000	0.069	0.061	0.047	e_{133}	0.084	0.046	0.071	0.069
e_{15}	0.073	0.061	0.068	0.048	e_{250}	0.004	0.009	0.069	0.024
e_{27}	0.072	0.070	0.070	0.032	e_{95}	0.071	0.069	0.041	0.025
e_{271}	0.072	0.036	0.065	0.069	e_{278}	0.082	0.051	0.049	0.070
e_{283}	0.078	0.042	0.069	0.027	e_{259}	0.076	0.066	0.045	0.074
e_{167}	0.060	0.045	0.069	0.055	e_{141}	0.005	0.063	0.030	0.065
e_{130}	0.054	0.067	0.063	0.068	e_{33}	0.080	0.036	0.070	0.060
e_{155}	0.000	0.071	0.062	0.073	e_{231}	0.007	0.072	0.029	0.070

e_{145}	0.077	0.055	0.059	0.043
e_{151}	0.007	0.042	0.055	0.059
e_{147}	0.057	0.022	0.057	0.062
e_{137}	0.056	0.069	0.057	0.037
e_{251}	0.007	0.064	0.066	0.049
e_{34}	0.007	0.054	0.071	0.053
e_{37}	0.007	0.018	0.072	0.074
e_{295}	0.007	0.006	0.029	0.071
e_{6}	0.001	0.065	0.026	0.061
e_{70}	0.081	0.028	0.000	0.068
e_{38}	0.001	0.068	0.065	0.034
e_{247}	0.004	0.003	0.052	0.050
e_{254}	0.002	0.064	0.027	0.071
e_{233}	0.060	0.070	0.065	0.066
e_{68}	0.085	0.039	0.036	0.066
e_{200}	0.084	0.033	0.044	0.070
e_{203}	0.083	0.061	0.048	0.066
e_{209}	0.003	0.056	0.058	0.069
e_{241}	0.003	0.061	0.058	0.058
e_{207}	0.084	0.032	0.054	0.069
e_{123}	0.003	0.069	0.008	0.064
e_{194}	0.085	0.057	0.057	0.062
e_{258}	0.078	0.016	0.053	0.068
e_{193}	0.003	0.069	0.037	0.063
e_{192}	0.003	0.059	0.039	0.067
e_{242}	0.078	0.069	0.068	0.026
e_{122}	0.002	0.069	0.033	0.048
e_{161}	0.002	0.068	0.064	0.046
e_{261}	0.001	0.036	0.039	0.071
e_{202}	0.083	0.070	0.030	0.052
e_{93}	0.003	0.044	0.053	0.068
e_{97}	0.085	0.069	0.060	0.068
e_{201}	0.079	0.037	0.060	0.060
e_{262}	0.071	0.037	0.061	0.000
e_{94}	0.081	0.022	0.066	0.018
e_{195}	0.067	0.013	0.069	0.038
e_{208}	0.002	0.070	0.060	0.071
e_{98}	0.080	0.070	0.069	0.055
e_{223}	0.002	0.070	0.068	0.060
e_{190}	0.003	0.008	0.053	0.041
e_{132}	0.003	0.069	0.055	0.043
e_{159}	0.070	0.041	0.070	0.030
e_{162}	0.084	0.056	0.063	0.062
e_{91}	0.080	0.067	0.024	0.060
e_{248}	0.002	0.070	0.070	0.062
e_{134}	0.078	0.025	0.071	0.068
e_{206}	0.002	0.070	0.058	0.070
e_{211}	0.085	0.070	0.071	0.048
e_{210}	0.081	0.070	0.064	0.047
e_{191}	0.003	0.046	0.064	0.037
e_{46}	0.002	0.019	0.054	0.063
e_{48}	0.002	0.046	0.068	0.063
e_{47}	0.071	0.069	0.046	0.058
e_{204}	0.077	0.064	0.070	0.049
e_{198}	0.002	0.053	0.071	0.021
e_{205}	0.002	0.005	0.071	0.062
e_{131}	0.071	0.032	0.069	0.036
e_{240}	0.085	0.054	0.058	0.048
e_{277}	0.002	0.072	0.044	0.062
e_{301}	0.004	0.072	0.068	0.048
e_{49}	0.002	0.069	0.067	0.063
e_{100}	0.002	0.058	0.041	0.061
e_{92}	0.002	0.067	0.060	0.067
e_{253}	0.002	0.049	0.053	0.041
e_{224}	0.085	0.000	0.069	0.059
e_{156}	0.002	0.018	0.066	0.064
e_{63}	0.083	0.033	0.035	0.063
e_{234}	0.082	0.067	0.059	0.054
e_{178}	0.072	0.041	0.036	0.069
e_{255}	0.083	0.056	0.064	0.052
e_{57}	0.003	0.066	0.041	0.044
e_{235}	0.078	0.059	0.068	0.058
e_{74}	0.055	0.069	0.050	0.054
e_{225}	0.000	0.008	0.066	0.054
e_{287}	0.084	0.069	0.071	0.025
e_{61}	0.000	0.070	0.070	0.064
e_{60}	0.002	0.070	0.023	0.037
e_{268}	0.002	0.029	0.042	0.057
e_{266}	0.002	0.008	0.036	0.052
e_{105}	0.070	0.056	0.054	0.070
e_{40}	0.003	0.067	0.054	0.065
e_{84}	0.085	0.069	0.071	0.069
e_{275}	0.002	0.068	0.037	0.059
e_{72}	0.065	0.026	0.043	0.067
e_{14}	0.086	0.069	0.061	0.067
e_{282}	0.075	0.069	0.071	0.055
e_{114}	0.004	0.069	0.066	0.039
e_{80}	0.002	0.042	0.067	0.054

e_{99}	0.058	0.031	0.066	0.065
e_{219}	0.002	0.071	0.074	0.071
e_{1}	0.004	0.074	0.063	0.076
e_{257}	0.001	0.018	0.069	0.030
e_{175}	0.001	0.070	0.062	0.075
e_{252}	0.003	0.066	0.040	0.054
e_{135}	0.001	0.067	0.044	0.062
e_{270}	0.086	0.047	0.057	0.071
e_{294}	0.002	0.023	0.070	0.061
e_{157}	0.001	0.068	0.072	0.061
e_{299}	0.002	0.066	0.070	0.059
e_{272}	0.006	0.068	0.044	0.042
e_{56}	0.004	0.032	0.032	0.024
e_{243}	0.005	0.064	0.028	0.030
e_{296}	0.002	0.066	0.068	0.069
e_{291}	0.004	0.064	0.063	0.057
e_{66}	0.059	0.063	0.049	0.067
e_{269}	0.004	0.044	0.052	0.040
e_{297}	0.006	0.059	0.075	0.043
e_{280}	0.004	0.068	0.090	0.048
e_{302}	0.002	0.070	0.070	0.049
e_{214}	0.004	0.067	0.036	0.064
e_{217}	0.000	0.072	0.071	0.047
e_{188}	0.055	0.060	0.014	0.067
e_{227}	0.077	0.070	0.021	0.050
e_{78}	0.080	0.036	0.001	0.070
e_{107}	0.083	0.051	0.021	0.059
e_{244}	0.067	0.070	0.029	0.039
e_{184}	0.072	0.070	0.034	0.072
e_{75}	0.085	0.069	0.054	0.056
e_{185}	0.075	0.046	0.053	0.050
e_{183}	0.086	0.008	0.041	0.062
e_{76}	0.005	0.070	0.038	0.030
e_{115}	0.085	0.040	0.042	0.067
e_{189}	0.086	0.070	0.066	0.055
e_{112}	0.006	0.054	0.055	0.063
e_{113}	0.082	0.070	0.063	0.055
e_{108}	0.069	0.020	0.068	0.073
e_{110}	0.063	0.031	0.064	0.067
e_{186}	0.077	0.070	0.059	0.066
e_{187}	0.006	0.057	0.069	0.036
e_{111}	0.066	0.062	0.067	0.068
e_{77}	0.086	0.065	0.068	0.024
e_{73}	0.016	0.067	0.070	0.071
e_{182}	0.007	0.030	0.071	0.072
e_{116}	0.005	0.070	0.072	0.043
e_{109}	0.085	0.070	0.071	0.057
e_{308}	0.002	0.086	0.110	0.108
e_{304}	0.002	0.082	0.090	0.047
e_{305}	0.003	0.007	0.095	0.076
e_{228}	0.007	0.047	0.059	0.069
e_{307}	0.006	0.072	0.083	0.042
e_{89}	0.089	0.060	0.031	0.075
e_{293}	0.001	0.074	0.053	0.080
e_{121}	0.002	0.087	0.057	0.081
e_{306}	0.007	0.100	0.099	0.116
e_{288}	0.007	0.054	0.094	0.104

Table 6

Global Ranking of Adjusters

Alternative	Global Score	Global Rank
e_{265}	79.02	1
e_{97}	78.91	2
e_{84}	77.88	3
e_{264}	77.36	4
e_{234}	77.34	5
e_{129}	77.09	6
e_{211}	76.4	7
e_{14}	75.99	8
e_{144}	75.68	9
e_{287}	75.51	10
e_{189}	75.11	11
e_{260}	74.89	12
e_{232}	74.56	13
e_{109}	74.38	14
e_{233}	74.32	15
e_{212}	73.84	16
e_{215}	73.81	17
e_{154}	73.8	18
e_{197}	73.79	19
e_{75}	73.69	20
e_{245}	73.68	21
e_{104}	73.36	22
e_{50}	73.11	23
e_{77}	73.1	24
e_{255}	72.74	25
e_{98}	72.49	26
e_{204}	72.22	27
e_{90}	72.11	28
e_{113}	72.03	29
e_{227}	72.01	30
e_{82}	71.8	31
e_{87}	71.8	32
e_{55}	71.64	33
e_{168}	71.6	34
e_{202}	71.35	35
e_{43}	71.29	36
e_{186}	71.27	37
e_{181}	70.88	38
e_{89}	70.67	39
e_{17}	70.56	40
e_{88}	70.4	41
e_{65}	70.4	42
e_{13}	70.39	43
e_{91}	70.31	44
e_{194}	70.04	45
e_{146}	70.03	46
e_{210}	69.85	47
e_{8}	69.69	48
e_{12}	69.63	49
e_{119}	69.63	50
e_{140}	69.51	51
e_{67}	69.44	52
e_{263}	69.31	53
e_{11}	69.13	54
e_{111}	68.97	55
e_{237}	68.91	56
e_{95}	68.72	57
e_{270}	68.48	58
e_{5}	68.03	59
e_{276}	67.63	60
e_{15}	67.58	61
e_{184}	67.42	62
e_{162}	67.19	63
e_{27}	66.98	64
e_{26}	66.9	65
e_{47}	66.8	66
e_{220}	66.73	67
e_{19}	66.73	68
e_{203}	66.57	69
e_{235}	66.34	70
e_{240}	66.33	71
e_{32}	66.05	72
e_{83}	65.86	73
e_{58}	65.68	74
e_{101}	65.33	75
e_{2}	65.16	76
e_{139}	64.79	77
e_{107}	64.7	78
e_{25}	64.41	79
e_{213}	64.37	80

e_{131}	64.24	81	e_{39}	55.21	125
e_{128}	64.05	82	e_{59}	55.2	126
e_{262}	63.99	83	e_{72}	54.91	127
e_{105}	63.92	84	e_{136}	54.88	128
e_{29}	63.67	85	e_{70}	54.65	129
e_{244}	63.54	86	e_{246}	54.43	130
e_{145}	63.34	87	e_{125}	54.2	131
e_{133}	63.34	88	e_{94}	52.98	132
e_{117}	63.3	89	e_{143}	52.89	133
e_{22}	63.17	90	e_{271}	52.58	134
e_{20}	62.81	91	e_{167}	52.38	135
e_{284}	62.77	92	e_{230}	52.02	136
e_{150}	62.56	93	e_{224}	51.75	137
e_{68}	62.52	94	e_{279}	51.73	138
e_{66}	62.48	95	e_{183}	51.68	139
e_{196}	62.28	96	e_{10}	51.67	140
e_{249}	62.26	97	e_{239}	51.57	141
e_{278}	62.25	98	e_{258}	50.86	142
e_{200}	62.17	99	e_{23}	50.34	143
e_{53}	62.14	100	e_{158}	50.3	144
e_{115}	62.09	101	e_{73}	50.11	145
e_{159}	62.07	102	e_{231}	49.78	146
e_{24}	61.35	103	e_{149}	49.44	147
e_{170}	60.33	104	e_{236}	49.2	148
e_{283}	60.14	105	e_{21}	48.71	149
e_{74}	59.37	106	e_{165}	48.66	150
e_{142}	58.81	107	e_{1}	48.36	151
e_{81}	58.8	108	e_{41}	47.99	152
e_{176}	58.79	109	e_{221}	47.77	153
e_{185}	58.78	110	e_{148}	47.34	154
e_{130}	58.69	111	e_{99}	47.24	155
e_{229}	57.99	112	e_{110}	47.03	156
e_{36}	57.66	113	e_{195}	46.21	157
e_{63}	57.58	114	e_{71}	46.06	158
e_{201}	57.46	115	e_{147}	45.12	159
e_{134}	57.45	116	e_{108}	44.08	160
e_{78}	56.6	117	e_{64}	43.88	161
e_{178}	56.4	118	e_{171}	43.49	162
e_{207}	56.37	119	e_{217}	43.17	163
e_{7}	56.24	120	e_{303}	42.97	164
e_{3}	56.1	121	e_{163}	42.97	165
e_{138}	55.98	122	e_{116}	42.4	166
e_{188}	55.85	123	e_{214}	41.89	167
e_{218}	55.54	124	e_{160}	41.67	168

e_{141}	41.63	169
e_{61}	41.37	170
e_{120}	41.26	171
e_{267}	41.1	172
e_{208}	41.05	173
e_{60}	41.03	174
e_{226}	41	175
e_{293}	40.87	176
e_{199}	40.78	177
e_{49}	40.78	178
e_{223}	40.72	179
e_{62}	40.72	180
e_{157}	40.6	181
e_{155}	40.59	182
e_{123}	40.57	183
e_{132}	40.4	184
e_{51}	40.37	185
e_{275}	40.29	186
e_{193}	40.22	187
e_{302}	40.2	188
e_{122}	40.05	189
e_{248}	39.97	190
e_{18}	39.95	191
e_{76}	39.87	192
e_{222}	39.75	193
e_{219}	39.71	194
e_{206}	39.58	195
e_{124}	39.45	196
e_{114}	39.41	197
e_{241}	39.28	198
e_{45}	39.15	199
e_{40}	39.09	200
e_{285}	39.08	201
e_{256}	38.84	202
e_{103}	38.78	203
e_{35}	38.73	204
e_{161}	38.7	205
e_{92}	38.65	206
e_{86}	38.64	207
e_{300}	38.28	208
e_{192}	38.18	209
e_{187}	37.96	210
e_{153}	37.87	211
e_{38}	37.83	212
e_{52}	37.63	213
e_{135}	37.35	214
e_{243}	36.27	215
e_{57}	36.24	216
e_{291}	36.02	217
e_{6}	35.7	218
e_{281}	35.57	219
e_{112}	35.49	220
e_{174}	34.96	221
e_{280}	34.68	222
e_{79}	34.29	223
e_{209}	34.15	224
e_{254}	34.08	225
e_{30}	33.89	226
e_{297}	33.19	227
e_{106}	33.12	228
e_{179}	32.59	229
e_{100}	32.19	230
e_{191}	31.36	231
e_{253}	31.3	232
e_{9}	31.06	233
e_{172}	30.09	234
e_{118}	29.69	235
e_{93}	29.16	236
e_{198}	29.01	237
e_{228}	27.74	238
e_{80}	27.59	239
e_{48}	26.31	240
e_{269}	25.65	241
e_{85}	25.06	242
e_{182}	24.86	243
e_{42}	24.6	244
e_{261}	23.88	245
e_{216}	22.79	246
e_{156}	22.72	247
e_{268}	22.72	248
e_{292}	22.39	249
e_{294}	22.24	250
e_{56}	21.99	251
e_{180}	21.83	252
e_{4}	20.14	253
e_{177}	18.12	254
e_{295}	17.66	255
e_{250}	17.39	256

e_{247}	16.82	257
e_{190}	16.8	258
e_{46}	16.8	259
e_{273}	15.48	260
e_{16}	14.86	261
e_{54}	13.65	262
e_{126}	13.02	263
e_{266}	10.61	264

5.3.2 Accident-type-based Adjuster Evaluation

At this phase, the TOPSIS and desirability functions mentioned in the methodology part were implemented on adjusters who examined files of the same accident type. To determine the type of new accidents in daily use of the company, a classification model has been developed that accepts accident types obtained from clustering in Part 5.2 as ground truth labels, trained with the same features used for clustering. *Scikit-learn* library classification algorithms (Pedregosa et al., 2011) were used for the development of models, and a 20-fold cross-validation procedure was conducted. The results are as shown in Table 7.

Table 7

20-fold Cross-Validation Results of Classification Model Training

Name	Mean Accuracy	Std Accuracy	Mean F1	Std F1
ExtraTrees	0.94	0.13	0.94	0.12
KNeighbors	0.94	0.13	0.93	0.12
MLP	0.95	0.1	0.93	0.1
Bagging	0.92	0.18	0.91	0.19
NearestCentroid	0.92	0.13	0.9	0.13
GaussianNB	0.74	0.06	0.61	0.05
RandomForest	0.56	0.07	0.29	0.04
SGD	0.25	0.03	0.18	0.02
DecisionTree	0.38	0.04	0.11	0.01
PassiveAggressive	0.17	0.04	0.09	0.02
AdaBoost	0.09	0.01	0.03	0
Dummy	0.01	0	0.01	0
ExtraTrees	0.94	0.13	0.94	0.12

After the cross-validation results were obtained, only the top three models with the highest mean F1 score were considered. Upon the recommendation of (Demšar, 2006), the Wilcoxon signed-rank test was applied for these models pairwise with %95 confidence level, and the Extra Trees was observed to be more performant than other classifiers (see Table 8). With this pipeline, after determining the new accident type with the trained Extra Trees classification model, the company can assign the best-performing and available adjuster to the new accident file using the accident type based on TOPSIS and the desirability method.

Table 8: Wilcoxon Signed Rank Test Results

Experiment (n=20)	*T*-Statistic	*P*
ExtraTrees vs. KNeighbors	26.0	0.003
ExtraTrees vs. MLP	39.0	0.013
KNeighbors vs. MLP	41.0	0.016

Verification

In this part, it is aimed to observe whether the system proposes better adjusters with better statistics and TOPSIS score as well. First, performance metrics with which the adjusters will be compared were determined with the decision-maker. Then, 1,000 files are selected randomly from the data, and for each file, adjuster ID, cluster no, and the performance of the adjuster. Since our system calculates adjuster's performance in a cluster in addition to an overall score, we also recorded these performances of top adjusters for each cluster. For verification, we compared the real performance and the performance of the adjuster which is proposed by our system for the related cluster. For each performance measure, average values of 1,000 files are given in Table 9.

Table 9
Verification results

Performance Measures	Real Performance	Performance of Proposed Adjusters	Improvement
File Closure Cost / Vehicle Value	11.01%	9.95%	9.59%
File Closure Time	20.13	19.83	1.47%
Percentage of Disclaim	0.29%	1.58%	447.58%
Percentage of Declines	1.38%	0.41%	70.51%
Overall Score	**34.79**	**94.07**	**170.36%**

In Table 9, the “Real Performance” column describes the average of performance metrics of the adjuster because of a realized assignment to accident files between January 2017 and July 2019 without using the proposed methodology. Besides, the “Performance of Proposed Adjusters” column describes the average performance of the best adjuster, which is selected with the help of the proposed method, according to the TOPSIS score. The success of the proposed method is demonstrated in the “Improvement” column. This table shows that there could be a significant difference if the company assigned the proposed adjusters to these files. For a better representation, Table 10 is prepared using the “Improvement” for the criterion calculated in Table X and the weight of the criterion, which reflects the percentage significance of the criterion for the insurance company. According to Table Y, the proposed method selects the best adjuster in harmony with weights or the need of the insurance company.

Table 10
Weights and the Improvement

Performance Measures	Weight	Improvement
File Closure Cost / Vehicle Value	6.2 %	9.59%
File Closure Time	7.7 %	1.47%
Percentage of Disclaim	25.4 %	447.58%
Percentage of Declines	21.8 %	70.51%

Conclusion

This study presented the methodology, application of the method on adjusters in the auto-insurance sector, and verification. It creates a connection between employees even if it is hard to compare them in a fair way to evaluate their performances. This connection exists only if features, their scales, methods that are suitable for your data, and criteria are analyzed well for the aim of your work.

In the methodology part, the main components are explained in detail. The flowchart is given to understand and follow the study easily. The study is in a specific sector, auto-insurance, but it is aimed that the study can be converted to any other sector easily where there is a need for a performance evaluation system for employees.

Also, a framework to evaluate adjusters’ performances of an insurance company is proposed. It is important to mention that deciding on important features for an accident, performance measures, and their weights were done after many interviews with the company and according to their aim. The results were obtained after applying the algorithm in the methodology part.

To verify our method, it was analyzed the possible performance improvements of adjusters by calculating the difference between the statistics of proposed adjusters by the system and the real statistics of randomly selected files. With the help of the system, when an accident file is opened, the company knows which adjusters worked on similar files and what were their performances. In the end, they also know the cumulative performance of their adjusters.

The study has also some potential limitations. Firstly, without improved data analysis knowledge, it is hard to decide which clustering or classification method is suitable for your data.

For future research, it is expected that this performance evaluation method will be used in different areas to support the performance evaluation problem of employees is not only for the auto insurance sector. It is expected that this study will be adjusted and applied easily for the other sectors.

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