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Cumulative belief degrees approach for analyzing the competitiveness of the automotive industry

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ABSTRACT

As traditional competition becomes global, businesses fail to take, on their own, the measures that are required to become more competitive. Hence, in a globally competitive environment, national improvement and competitiveness have also become vital. Businesses must utilize and be supported by the international competitiveness of their nations. This study aims to analyze the competitiveness of the automotive industry from a national competitiveness perspective, using a three-stage methodology. For this purpose, a novel cumulative belief degrees (CBD) approach is introduced, to quantify the causal relations among the variables in the system. This methodology is illustrated by the analysis of the Turkish automotive industry for developing suggestions to assist policymakers in their decisions to improve the competitiveness of the industry. Although the findings are country specific, the methodology is applicable to a wider range of industries in developed and developing countries.

1. Introduction

Competition at the international level has increased greatly in significance for all countries since the globalization of the world economy. The basic aim of policymakers is to bring the economy of their countries onto a competitive footing and, thus, to increase the welfare of their society. Competitiveness is generally defined as the set of institutions, policies and relevant factors that determine the level of productivity of a country [3]. Each year, selected organizations, such as the World Economic Forum (WEF) and the Institute for Management Development (IMD), apply several hundreds of objective and subjective indicators to assess the wealth created by the world's nations and, subsequently, publish rankings of national competitiveness. These rankings serve as a benchmark for policymakers and other interested parties, for judging the competitive success of their country within a global context.

As traditional competition becomes global, businesses fail to take the required measures on their own to become more competitive. In fact, an increase in competitiveness cannot be realized based solely on the effort of a specific industry. Hence, in a globally competitive environment, national improvement must also become vital. Therefore, it is the responsibility of governments to increase the competitive advantage of industries. To offer a competitive edge to firms, governments must take action to increase the respective industry's competitiveness, given the current competitiveness level of the nation. According to Sala-i Martin [22], national competitiveness in terms of a macroeconomic environment, higher education level, labor market efficiency, financial market development, technological readiness, business sophistication, and innovation level are very important for the success of an industry.

When working at the industry level, there are a number of factors, such as education, infrastructure, and business sophistication, that can be manipulated by the government to increase the industry's competitiveness. Usually, such factors are interrelated, and it is a scientific problem to quantify the causal relationships among them. Initially, it is necessary to produce clarity and insight by modeling and quantifying the causal relations among the factors that affect the competitiveness of an industry. Then, it will be possible for governments to make informed policy decisions, to improve the competitiveness of the industry in question.

In parallel with these assertions, this study analyzes the system of the automotive industry, based on the assessment of the national competitive advantage. The WEF indicators for the competitiveness of nations are considered to be the fundamental source of criteria for the competitiveness of the automotive industry. The factors that affect the competitiveness of an industry

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are interrelated, and quantification of the causal relations among these factors emerges as a challenge that is addressed by this paper.

This study aims to develop a decision-making tool to support the policymakers in their decisions to improve a given industry. The proposed methodology enables them to facilitate the selection and prioritization of policies to be followed by their respective governments. For the purpose of illustration, the methodology is applied to the Turkish automotive industry. The main reason for selecting this industry is its locomotive effect on the whole economy of most of the developed and developing countries, including Turkey. This effect is mainly the result of its close relation with other industries in the economy. The automotive industry is the main buyer for the iron and steel, petrochemical, and tire industries and is the driving force behind technological development in these industries. All of the types of motor vehicles that are needed by the tourism, infrastructure, transport and agriculture industries are produced by this industry. Therefore, any change in this industry deeply affects the economy as a whole, and hence, its competitiveness plays an important role for the country.

The secondary aim of this study is to propose a novel approach, called the cumulative belief degree (CBD) approach, for the quantification of causal relations among variables in a system. By using this approach, the competitiveness of the automotive industry can be analyzed, based on the primary national competitiveness factors that influence the automotive industry's performance.

Therefore, the main contributions of this study can be listed as follows:

- a novel approach for the quantification of causal relations;
- a three-stage methodology for analyzing the competitiveness of an industry; and
- an application of the proposed methodology to the automotive industry. For this aspect, the system of the automotive industry is structured, the causal relations in the system are quantified using the CBD approach, and policy suggestions are developed.

This paper is organized as follows. The second section summarizes the related literature. The third section introduces the CBD approach that is developed for the quantification of causal relations in a system. The fourth section presents the details of the proposed methodology and provides its application to the Turkish automotive industry. Finally, the paper concludes with policy suggestions in the fifth section.

2. Literature review

2.1. Competitiveness of the automotive industry

There are few studies on assessing the competitiveness in an automotive industry. Evidence from the Polish automotive industry suggests that the knowledge transfer from transnational corporations improves the performance of local suppliers and, subsequently, their ability to compete [23]. Tcha and Kuriyama [27] analyze the effects of government policies on the Australian automotive industry, using a partial equilibrium model. The authors warn that the globalization of the world automotive market will decrease the prices, and consequently, the expected welfare effects of government policies will depend on each country's tariff rates as well as its manufacturing costs. In a similar study, Williamson [30] investigates the relationship between exchange rate exposure and competition in the automotive industry. Evidence supports the theoretical determinants of foreign exchange rate exposures for firms in the globally competitive automotive industry.

Sirikrai and Tang [24] suggest a four-level Analytical Hierarchy Process (AHP) model to analyze the competitiveness of the automotive components industry in Thailand, where at the base level, the sub-elements of competitive conditions—namely, the government roles, managerial resources and technological capabilities—are compared. However, owing to the nature of the method employed, this study cannot capture the interactions between the variables of the model. A comparable study by Laosirihongthong and Dangayach [14] presents an empirical analysis of the implementation of manufacturing strategies in Thai and Indian automotive manufacturing companies. In these countries, the priorities of the companies when attempting to be competitive are improving product and process-related quality and on-time delivery.

Table 1 provides a summary of previous research that involves attempting to explain the competitiveness of the automotive industry, including the methods used for that purpose.

This literature review shows that the indicators and drivers of competitiveness are multifaceted in nature, with complex relationships. Therefore, single or a few aspects will not be sufficient to explain competitiveness thoroughly at the industrial or national level. In general, previous studies analyzed only the impact of the technology [8,29] or knowledge transfer [16] on the competitiveness. However, the competitiveness level of the industry depends on the global competitiveness level of the related country. In the literature, this linkage is shown only for some specific indicators of global competitiveness, but this paper attempts to explain industry level competitiveness, with a comprehensive holistic approach encompassing all of the factors that constitute the country-level competitiveness. The automotive industry is selected specifically, as an example to show this linkage, owing to its significant role in the economy. To highlight the relationship between the global competitiveness of a country and the competitiveness of the industry of interest, a causal mapping approach combined with a CBD approach is used in this study.

2.2. Causal mapping approach

Causal knowledge based on causal analysis increases the quality of decision-making in most real-world situations [33]. Utilizing causal modeling helps to develop an explanation of relationships and to provide a basis for inference [2]. It links strategic thinking and acting, helps make sense of complex problems, and communicates these aspects to others [7]. Causal relationships can be used effectively to develop inferences for diagnostic reasoning from

Table 1
Studies on the competitiveness of the automotive industry.

Determinants of competitive advantage	Method	Authors
Exchange rate exposure	Econometric models	Williamson [30]
Government policies	Econometric models	Tcha and Kuriyama [27]
Quality, delivery, flexibility, cost	Survey, inferential statistics	Laosirihongthong and Dangayach [14]
Industrial competitive conditions, governmental roles, managerial resources, technology capabilities	Analytical hierarchy process	Sirikrai and Tang [24]
Knowledge transfer	Survey, inferential statistics	Simona and Axèle [23]

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effects to causes and for the prediction of outcomes that would follow from a policy or procedure intervention.

Causal knowledge is concerned with the configuration of a given system and the way that its components work together to perform a specific task [1]. Causal maps visualize the relationships among concepts by connecting them with labeled arrows. The determination and quantification of the cause and effect relationship is not easy because the interaction between the cause and effect is often complex and understated [15]. There is a variety of different techniques that are used for causal modeling. Bayesian networks and structural equation modeling (SEM) are among the most frequently used techniques for building causal maps [33]. Graphical causal models can be used for constructing partial information, using observational data, even when some of the variables in the causal graph are not measured [26].

A Bayesian network approach can be used to make inferences in causal maps [17]. There are a number of studies in which Bayesian causal maps have been used to support policy making. For example, Bacon et al. [4] use a Bayesian Network approach to develop effective policies for more sustainable rural land use and development, incorporating several different stakeholder viewpoints and demonstrating the crucial roles of beliefs and uncertainties in determining the preferred options.

The SEM is a causal modeling approach that is based on cause and effect reasoning. It allows for simultaneous examination of relationships among multiple independent variables and multiple dependent variables and estimates model parameters in latent variables [12]. Thus, it can be used to make evaluations of a network of relationships between manifest and latent variables. SEM modeling is widely used. However, it falls short of incorporating missing and fuzzy data, because it is built using available deterministic data.

The main difficulty with the models described above concerns the impossibility of incorporating the uncertainty that is observed in real-life problems, whereas the causal model represents such problems. Usually, uncertainties are encountered in the parameters, initial conditions, and model structure (i.e., the relations among its variables, the functional forms, the causal influences, and delays), as well as the pertinence of the model (i.e., its level of granularity, selection of variables, closeness, time scale; [6].

In this study, a CBD approach is used to alleviate the quantitative uncertainty by allowing fuzzy assessments of model parameters and conditions. As is well known, the strength of fuzzy logic is that it can mimic the ability of the human mind and applies this ability to employ modes of effective reasoning that are approximate rather than exact [34]. Building on these ideas, the CBD approach was developed originally for the evaluation of nuclear safeguards, based on fuzzy linguistic terms and belief structure [10]. This approach is based on representing any information by a belief structure that uses linguistic terms. The basic strength of the approach is that it allows the user to aggregate data when uncertainty arises. Moreover, it can handle data that are at different scales as well as expert opinions in different formats. The CBD approach can also address values that are missing because of a lack of expertise or a scarcity of information. Finally, CBD helps to perform analysis that uses linguistic terms, and it can provide linguistic results that are more understandable for the policymakers.

3. CBD approach for the quantification of causal relations

The CBD approach was developed initially for the evaluation of nuclear safeguards [10]. This approach also has applications in multiple-criteria decision-making problems [11,20]. The basic use of CBDs is to enable mathematical operations on belief structures. In this research, CBDs are used to quantify the causal relations among the variables in the system. For example, suppose that an attempt is made to analyze the relations in a system that is composed of four variables, as given in Fig. 1. In the given system, A and C are inputs and D is the output. The aim here is to quantify the given relations (i.e., A → B; B → D; C → D) in such a way that interpretations about the output can be made when the inputs are changed.

The relations in such a system can be quantified by the use of past data and/or expert opinions. In this approach, all of the data and/or expert opinions that are used to quantify the relations are assumed to be represented by belief structures and linguistic terms. Given the fact that the information in most of the different formats can be converted to belief structures without loss of information [10], this assumption is valid.

3.1. CBD defined

In this study, fuzzy linguistic terms [35] are used to represent the information by the belief structure. Let $S = \{s_i\}$, $i \in \{0, \ldots, m\}$ be a finite and totally ordered term set. Any label, s_i, represents a possible value for a linguistic variable. The semantics of the finite term set S are given by fuzzy numbers, which are defined in the [0,1] interval, and by their membership functions. Linguistic term sets can be defined according to the nature of the problem. For this study, the competitiveness indicators (variables in the system) are evaluated with a five-term set, $S = \{s_i\}$, $i \in \{0, \ldots, 4\}$, in which the following meanings are assigned to the terms: s_0: very low; s_1: low; s_2: medium; s_3: high; and s_4: very high.

The belief structure is used to represent the general belief of the level of an indicator, as a result of past data or expert evaluations. Therefore, if the past data of an indicator is available, then the fuzzy linguistic sets are defined for the data as well as the membership degrees of evidence to the fuzzy sets. For example, consider the instance with 20% to s_1 and 80% to s_2. In this statement, s_1 and s_2 are linguistic evaluation grades, and the percentage values of 20% and 80% are membership degrees that are referred to as the degrees of belief, which indicate the extent to which the corresponding grades are assessed. The above assessment can be expressed as the following expectation:

$$B(I_1) = \{(0.2, s_1), (0.8, s_2)\} \tag{1}$$

where $B(I_1)$ stands for the state of the level of the first indicator. Note that the belief degrees for linguistic terms s_0, s_3, and s_4 are zero. Therefore, they are not shown in Eq. (1). In general, the belief structure can be defined as follows:

$$B(I_k) = \{(\beta_{ik}, s_i), i = 0, \ldots, m)\}, \ \forall k, \quad \sum_{i=0}^{m} \beta_{ik} \leqslant 1, \forall k \tag{2}$$

where k and i are indices for indicators and linguistic terms, respectively, and β_{ik} is the belief degree for the level of indicator k at the level s_i.

The CBD at certain linguistic term levels can be defined as the aggregated belief degrees with greater or equal terms with respect

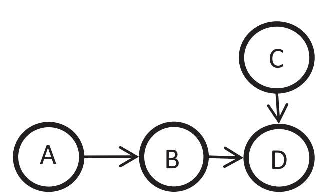

Fig. 1. An example of a system with four variables.

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to the related linguistic term. The cumulative belief structure can be defined as follows:

$$C(I_k) = \{(\gamma_{ik}, s_i),\ i = 0, \ldots, m)\},\ \forall k, \quad \gamma_{ik} = \sum_{j=i}^{m} \beta_{jk} \tag{3}$$

where γ_{ik} is CBD related to indicator k at threshold level i. For example, for $B(I_1) = \{(0.2, s_1), (0.8, s_2)\}$, the corresponding cumulative belief structure is $C(I_1) = \{(1, s_0), (1, s_1)(0.8, s_2), (0, s_3), (0, s_4)\}$, where γ_{21}, which is CBD related to linguistic term s_2, is calculated as follows:

$$\gamma_{21} = \beta_{21} + \beta_{31} + \beta_{41} = 0.8 + 0 + 0 = 0.8.$$

3.2. Proposed CBD approach

The proposed approach assumes that there is a system of interrelated variables (or indicators). The aim is to quantify the relations, given the past data or expert judgments that are represented by or converted to CBDs. Suppose that N is the set of relations between the indicators, such that if indicator l affects indicator k, then $(l,k) \in N$. Then, w_{ij}^{kl}, the importance weight that is related to the relation (l,k), is found by using the following equation:

$$\gamma_{ik} = \sum_{l|(l,k)\in N} \sum_j \gamma_{jl} w_{ij}^{kl} \quad \forall i, k \tag{4}$$

where i and j are indices for linguistic terms (i corresponds to indicator k, and j corresponds to indicator l). Here, the CBD of any indicator at each linguistic term set level is affected by CBDs of the affecting indicators at all of the linguistic term set levels.

The importance weights can be derived from the given data and/or expert opinion as a regression-based model, as follows.

For k, which is an affected indicator; and for l, which is an affecting indicator of k.

$$\begin{aligned}
&\text{Find} \quad w_{ij}^{kl}, \forall i \\
&\text{By minimizing} \quad \sum_i \sum_n (e_{ik}^n)^2 \\
&\quad \text{Subject to} \quad e_{ik}^n = \gamma_{ik}^n - \sum_{l|(l,k)\in N} \sum_j \gamma_{jl}^n w_{ik}^{jl} \\
&\qquad\qquad\qquad \sum_l \sum_j w_{ij}^{kl} = 1 \quad \forall i \\
&\qquad\qquad\qquad w_{ij}^{kl} \geqslant 0, \quad \forall k,\ \forall l,\ \forall i,\ \forall j
\end{aligned} \tag{5}$$

where n is an index for the evident data, and e_{ik}^n is the error that is related to dataset n for calculating γ_{ik}. This model can be solved in a way that is similar to a classical regression model (see [9], for finding parameters in regression models) or by any non-linear optimization method, such as Newton's method (see [5], for details of the method.)

3.3. Illustrative example

For illustration purposes, assume that we have the system given in Fig. 1, with the belief degrees in Table 2. To analyze the given system, the proposed model is run for indicators B and D, which are the affected indicators. As an example, the model is built for indicator D. For this purpose, the belief degrees are first converted to CBDs, as in Table 3.

Then, the proposed model is formulated as follows:

$$\begin{aligned}
&\text{For} \quad k = D, l = B, C; \\
&\text{Find} \quad w_{ij}^{DB}, w_{ij}^{DC} \quad \forall i, j \\
&\text{By minimizing} \quad \sum_{i=0}^{4} \sum_{n=1}^{5} (e_{ik}^n)^2 \\
&\quad \text{Subject to} \quad e_{iD}^n = \gamma_{iD}^n - \sum_{l=B,C} \sum_j \gamma_{jl}^n w_{iD}^{jl} \quad \forall i, n \\
&\qquad\qquad\qquad \sum_{l=B,C} \sum_{j=0}^{4} w_{ij}^{kl} = 1 \quad \forall i \\
&\qquad\qquad\qquad w_{ij}^{Dl} \geqslant 0, \quad l = B, C,\ \forall i,\ \forall j
\end{aligned} \tag{6}$$

When the given model is solved by using the Excel Solver, the weights in Table 4 are found.

According to the results given in Table 4, because the sum of the weights related to indicator B and indicator C is 1.576 (=.8 + .1 + .5 + .1 + .005 + .71) and 3.423 (=.1 + .099 + .299 + .001 + .001 + .26 + .663 + .079 + .901 + .020 + 1), respectively, indicator D is mostly affected by C compared to B.

These weights can then be used to find the value of D when there are new input values for B and C. For example, if B is $\{(s_3,.5),(s_4,.5)\}$ and C is $\{(s_2,.6),(s_3,.4)\}$ (i.e., the related CBDs are $I_B = \{(s_0,1),(s_1,1),(s_2,1),(s_3,1),(s_4,.5)\}$, $I_C = \{(s_0,1),(s_1,1),(s_2,1),(s_3,.4),(s_4,0)\}$), then D is found to be $\{(s_0,1),(s_1,1),(s_2,1),(s_3,0.44),(s_4,0)\}$. For example, γ_{3D} is calculated as follows:

$$\begin{aligned}
\gamma_{3D} &= \sum_{l=B,C} \sum_j \gamma_{jl} w_{3j}^{Dl} = (\gamma_{0B} w_{30}^{DB} + \gamma_{1B} w_{31}^{DB} + \gamma_{2B} w_{32}^{DB} + \gamma_{3B} w_{33}^{DB} \\
&\quad + \gamma_{4B} w_{34}^{DB}) + (\gamma_{0C} w_{30}^{DC} + \gamma_{1C} w_{31}^{DC} + \gamma_{2C} w_{32}^{DC} + \gamma_{3C} w_{33}^{DC} + \gamma_{4C} w_{34}^{DC}) \\
&= (1 \cdot 0 + 1 \cdot 0 + 1 \cdot 0 + 1 \cdot 0 + .5 \cdot 0) + (1 \cdot 0 + 1 \cdot 0 + 1 \cdot .079 \\
&\quad + .4 \cdot .901 + 0 \cdot .020) = .44
\end{aligned}$$

When the CBD of D is converted to the belief structure in this example, the belief structure is found to be $\{(s_2,56),(s_3,0.44)\}$. Finally, the following linguistic conclusion can be derived: if B is between high (s_3) and very high (s_4) and C is between medium (s_2) and high (s_3), then D will be between medium (s_2) and high (s_3).

The CBD approach introduced in this section is used as the second stage (quantification of causal relations) of the methodology proposed in this paper. The details of the application process is explained in Section 4.

4. Proposed methodology and its application to the Turkish automotive industry

In this study, a three-stage methodology is proposed, to assess the competitiveness of the Turkish automotive industry and to analyze the impact of possible alternative policies (Fig. 2). In the problem-structuring stage, WEF indicators related to the

Table 2
Belief degrees of the past data for the illustrative example.

n	A	B	C	D
1	$\{(s_0,.8), (s_1,.2)\}$	$\{(s_1,.6), (s2,.4)\}$	$\{(s1,.9), (s2,.1)\}$	$\{(s1,.8), (s2,.2)\}$
2	$\{(s_1,.6), (s_2,.4)\}$	$\{(s_2,.7), (s3,.3)\}$	$\{(s2,1)\}$	$\{(s2,.9), (s3,.1)\}$
3	$\{(s_2,.4), (s_3,.6)\}$	$\{(s_3,.5), (s4,.5)\}$	$\{(s0,1)\}$	$\{(s0,.3), (s1,.7)\}$
4	$\{(s_3,.5), (s_4,.5)\}$	$\{(s_3,.2), (s4,.8)\}$	$\{(s1,.5), (s2,.5)\}$	$\{(s1,.1), (s2,.9)\}$
5	$\{(s_1,.4), (s_2,.6)\}$	$\{(s_2,.5), (s3,.5)\}$	$\{(s2,.2), (s3,.8)\}$	$\{(s2,.2), (s3,.8)\}$

Table 3
CBDs for the illustrative example.

n	B					C					D				
	s_0	s_1	s_2	s_3	s_4	s_0	s_1	s_2	s_3	s_4	s_0	s_1	s_2	s_3	s_4
1	1	1	.4	0	0	1	1	.1	0	0	1	1	.2	0	0
2	1	1	1	.3	0	1	1	1	0	0	1	1	1	.1	0
3	1	1	1	1	.5	1	0	0	0	0	1	.7	0	0	0
4	1	1	1	1	.8	1	1	.5	0	0	1	1	.9	0	0
5	1	1	1	.5	0	1	1	1	.8	0	1	1	1	.8	0

Table 4
Calculated weights for the illustrative example.

	w_{i0}^{DB}	w_{i1}^{DB}	w_{i2}^{DB}	w_{i3}^{DB}	w_{i4}^{DB}	w_{i0}^{DC}	w_{i1}^{DC}	w_{i2}^{DC}	w_{i3}^{DC}	w_{i4}^{DC}
w_{0j}^{DI}	.800	.100	0	0	0	.100	0	0	0	0
w_{1j}^{DI}	.500	.100	0	0	0	.099	.299	.001	.001	0
w_{2j}^{DI}	0	0	.005	.071	0	0	.260	.663	0	0
w_{3j}^{DI}	0	0	0	0	0	0	0	.079	.901	.020
w_{4j}^{DI}	0	0	0	0	0	0	0	0	0	1.000

automotive industry are selected, and expert judgments are used to establish the causal relations among the indicators. Then, the novel CBD approach, details of which are given in Section 3, is used to quantify these causal relations among the system variables (i.e., the WEF indicators). Based on the results of the CBD approach, the policy alternatives, together with possible outcomes, are developed in the third stage. Details of this framework are explained in the subsequent sections.

4.1. Problem structuring

The problem structuring phase for the analysis of competitiveness of the automotive industry is demanding, owing to the technical complexity, degree of uncertainty, and divergence of values and interests of different stakeholders. There are many factors that can be included in the system, and it is very difficult to formulate the relationships among them by using classical hard system approaches. The industry affects and is affected by various stakeholders, including the government, other industries, such as the steel industry and tire industry, suppliers, universities, exporters, importers, and customers. Therefore, a Delphi type [21,19] soft group decision-making approach is used, to specify the relations in the system under study after determining the indicators.

4.1.1. WEF competitiveness indicators

In the problem-structuring phase, the components (called "indicators" in the related reports, such as the WEF Global Competitiveness Report) in the case of the Turkish automotive industry, were determined. A survey was conducted with the members of the automotive industry stakeholders, to reveal the WEF indicators that are the most significant to the industry. Because there could be a variety of different components of the system, and they can be stated in very different ways, possible components were listed in the survey. The survey included 111 indicators of the WEF Global Competitiveness Report [22]. Because the WEF report classifies the indicators in 12 basic pillars, this study follows a similar principle, and the survey asked the respondents the importance of these indicators on the basis of these 12 pillars. The twelve pillars are as follows:

1. Institutions (19 indicators)
2. Infrastructure (8 indicators)
3. Macroeconomic Environment (5 indicators)
4. Health and Primary Education (11 indicators)
5. Higher Education and Training (8 indicators)
6. Goods Market Efficiency (15 indicators)
7. Labor Market Efficiency (9 indicators)
8. Financial Market Development (9 indicators)
9. Technological Readiness (9 indicators)
10. Market Size (2 indicators)
11. Business Sophistication (9 indicators)
12. Innovation (7 indicators)

Furthermore, an online survey was conducted, asking respondents to evaluate the impact of each WEF indicator on the competitiveness of the automotive industry, on a scale of 1–10. A total of 72 responses were received from a wide spectrum of participants, including members of the Automotive Manufacturers Association (OSD), suppliers, and distributors and authorized dealers who are involved in the supply chain, a select group of related bureaucrats, press/media members, employees of financial and private research institutions, and academics.

Later, all of the indicators were ranked in descending order, and those that scored 8.5 and higher were featured in the structure of the problem. The cut-off point (which was 8.5) was decided based on the consensus of the top executives from the Federation of Industrial Associations (SEDEFED), TÜSİAD Sabanci University Competitiveness Forum (REF), and OSD. The rationale was that the analysis of the results also indicated a larger gap between the indicators' scores below 8.5.

According to the results of the survey, 15 indicators given in Table 5 (the indicators ID# 1 to #15) were agreed upon, to have an impact on the future of competitiveness of the automotive industry.

The results of the survey were then discussed with executives from SEDEFED, REF and OSD, the main stakeholders of the automotive industry. It was decided to add several other indicators from the WEF list that are specific to the automotive industry. These indicators are given in the last three rows of Table 5 (the indicators with ID #16 to #18).

As a result, 18 indicators are specified in the problem structure of the competitiveness of the automotive industry.

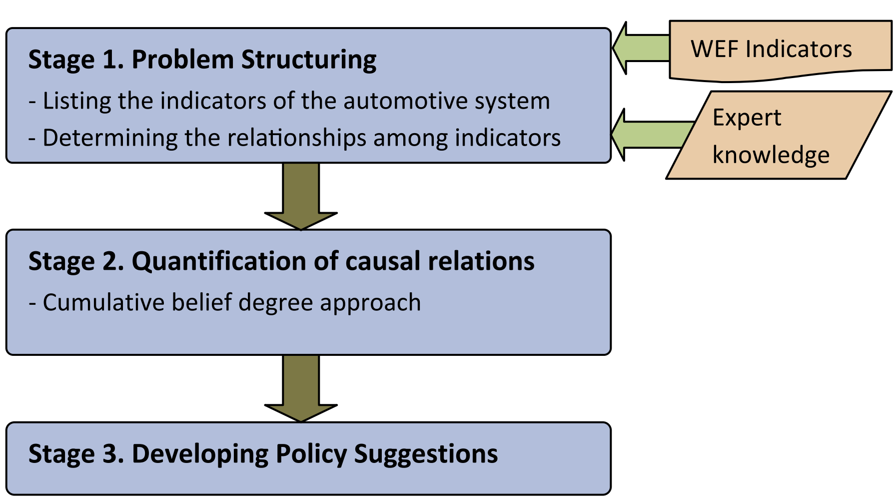

Fig. 2. Framework of the proposed methodology.

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Table 5
Indicators identified based on expert opinions.

ID #	Indicator	Explanation	Data type
1	Domestic market size index	The size of the domestic market is constructed by taking the natural log of the sum of the gross domestic product valued at the purchased power parity (PPP), plus the total value (PPP estimates) of the imports of goods and services, minus the total value (PPP estimates) of the exports of goods and services. Data are then normalized on a 1–7 scale. PPP estimates of imports and exports are obtained by taking the product of the exports as a percentage of the GDP and taking the GDP valued at the PPP	1–7 scale
2	Foreign market size index	The size of the foreign market is estimated as the natural log of the total value (PPP estimates) of exports of goods and services, which is normalized on a 1–7 scale. PPP estimates of exports are obtained by taking the product of the exports as a percentage of the GDP and the GDP valued at the PPP	1–7 scale
3	Capacity of Innovation	This indicator is measured through WEF's annual Executive Opinion Survey. It answers the question: In your country, how do companies obtain technology? [1 = exclusively from licensing or imitating foreign companies; 7 = by conducting formal research and pioneering their own new products and processes]	1–7 scale
4	Quality of scientific research institutions	This indicator is measured through WEF's annual Executive Opinion Survey. It answers the question: How would you assess the quality of scientific research institutions in your country? [1 = very poor; 7 = the best in their field internationally]	1–7 scale
5	Company spending on R&D	This indicator is measured through WEF's annual Executive Opinion Survey. It answers the question: To what extent do companies in your country spend on R&D? [1 = do not spend on R&D; 7 = spend heavily on R&D]	1–7 scale
6	Availability of scientists and engineers	This indicator is measured through WEF's annual Executive Opinion Survey. It answers the question: To what extent are scientists and engineers available in your country? [1 = not at all; 7 = widely available]	1–7 scale
7	University-industry collaboration in R&D	This indicator is measured through WEF's annual Executive Opinion Survey. It answers the question: To what extent do business and universities collaborate on research and development (R&D) in your country? [1 = do not collaborate at all; 7 = collaborate extensively]	1–7 scale
8	Local supplier quality	This indicator is measured through WEF's annual Executive Opinion Survey. It answers the question: How would you assess the quality of local suppliers in your country? [1 = very poor; 7 = very good]	1–7 scale
9	Production process sophistication	This indicator is measured through WEF's annual Executive Opinion Survey. It answers the question: In your country, how sophisticated are production processes? [1 = not at all; labor-intensive methods, or previous generations of process technology prevail; 7 = very; the world's best and most efficient process technology prevails]	1–7 scale
10	Firm-level technology absorption	This indicator is measured through WEF's annual Executive Opinion Survey. It answers the question: To what extent do businesses in your country absorb new technology? [1 = not at all; 7 = aggressively absorb]	1–7 scale
11	Availability of latest technologies	This indicator is measured through WEF's annual Executive Opinion Survey. It answers the question: To what extent are the latest technologies available in your country? [1 = not available; 7 = widely available]	1–7 scale
12	Ease of access to loans	This indicator is measured through WEF's annual Executive Opinion Survey. It answers the question: How easy is it to obtain a bank loan in your country with only a good business plan and no collateral? [1 = very difficult; 7 = very easy]	1–7 scale
13	Extent and effect of taxation	This indicator is measured through WEF's annual Executive Opinion Survey. It answers the question: What impact does the level of taxes In your country, have there been incentives to work or invest? [1 = significantly limits incentives to work or invest; 7 = has no impact on incentives to work or invest]	1–7 scale
14	Total tax rate	This indicator is a combination of profit tax (% of profits), labor tax and contribution (% of profits), and other taxes (% of profits)	Percentage (%)
15	Degree of customer orientation	This indicator is measured through WEF's annual Executive Opinion Survey. It answers the question: How do companies in your country treat customers? [1 = generally treat their customers badly; 7 = are highly responsive to customers and customer retention]	1–7 scale
16	Domestic automotive market size	The number passenger cars per 1,000 people. Data is provided by http://data.worldbank.org/. Passenger cars refer to road motor vehicles, other than two-wheelers, intended for the carriage of passengers and designed to seat no more than nine people (including the driver)	Numeric
17	Automotive foreign market effectiveness	Revealed Competitiveness Index for automotive industry. Data is provided from REF. It is equal to the logarithmic difference between the Export Advantage Index and the Import Advantage Index. A positive value reflects comparative advantage, whereas negative values reflect comparative disadvantage	Numeric
18	Automotive production process sophistication	Revealed Comparative Advantage. This indicator is the ratio of automotive exports to total exports in the country. Data is provided from REF. This indicator is one of 9 parameters suggested by Turkish State Planning Institute. This parameter is calculated as: the (export level of a specific industry / the total export of the related country) / (the world export level of the specific industry /the world total export level	Numeric

4.1.2. Relationships of the indicators

After the indicators of the automotive industry are specified, it is crucial to reveal connections among them to conceptualize the relationships among the components in the problem. The connections of the indicators are revealed through a Delphi type [21,19], soft group decision-making approach.

A workshop with 29 participants was organized to obtain the perceptions of the stakeholders, related to the problem structure. Similar to the survey, the participants included a wide range of academics, key people from the automotive industry, non-governmental organizations/consultants, subsidiary industries, and public and press figures, to enable different perspectives on the subject. The workshop lasted one full day and took place in four phases. In the first phase, an informative presentation on the study, the process and the indicators were given to the participants. In the second phase, the participants were grouped randomly, to ensure homogeneity, and each group was asked whether there was a connection among the indicators in a pair-wise manner. They were instructed to evaluate the relations on a scale of -3 to +3, where these concepts were featured in this relationship (see Table 6 for the definitions of the scale).

After the second phase, the results of the groups were summarized in terms of the first quadrant, second quadrant, median, and amplitudes for every indicator in the survey. In the third phase, the participants were again given the previous survey, only this time, the results of all of the groups were provided as extra information. The participants were asked to compare their answers to the group statistics and to review their decisions. This stage enabled the groups to think about different perspectives and to find out a compromise on the relationships. The resulting causal map is given in Fig. 3.

The final result of the workshop (i.e., the causal relations between the indicators) is summarized in Table 7. The third column of the table shows the relations between indicators. For example,

Table 6
Linguistic expressions used in the workshop.

Scale levels	Linguistic expression
+3	Strong positive relation
+2	Moderate positive relation
+1	Weak positive relation
0	No relation
−1	Weak negative relation
−2	Moderate negative relation
−3	Strong negative relation

Table 7
Indicators and causal relations determined in Stage 1.

ID #	Indicator	Affecting indicator(s)
1	Domestic market size index	12, 13, 14, 16
2	Foreign market size index	1, 17
3	Capacity of Innovation	4
4	Quality of scientific research institutions	5, 6
5	Company spending on R&D	13, 14
6	Availability of scientists and engineers	13
7	University–industry collaboration in R&D	3, 4, 5, 14
8	Local supplier quality	3, 4, 11
9	Production process sophistication	5, 7, 8
10	Firm-level technology absorption	3, 5, 7
11	Availability of latest technologies	7, 10
12	Ease of access to loans	
13	Extent and effect of taxation	
14	Total tax rate	
15	Degree of customer orientation	9
16	Domestic automotive market size	8, 12, 13, 14
17	Automotive foreign market effectiveness	15
18	Automotive production process sophistication	10, 16, 17

#2 *Foreign market size index* is affected by #1 *Domestic market size index* and #17 *Automotive foreign market effectiveness*.

4.2. Quantification of causal relations

Relations found in the previous stage are quantified by using a CBD approach. For this purpose, the data on 28 countries are provided, as obtained from the WEF [32] report, and are considered as input. The data were initially normalized in a 0–1 interval (the best score is 1 and the worst score is 0), for the purpose of converting them to a belief structure. Then, the membership values of the normalized scores are calculated, according to the fuzzy sets defined in Fig. 4. These membership values constitute the belief degrees for each datum. For example, if the normalized score is 0.55, then the related belief structure is $B(I) = \{(s_2, .8), (s_3, .2)\}$ (see Fig. 4).

The proposed CBD approach is formulated for 15 indicators that are affected by other indicators (i.e., all of the indicators except for #12, #13, and #14). For example, for indicator #9 *production process sophistication*, the affecting indicators are #5 *company spending on R&D*, #7 *university-industry collaboration in R&D*, and #8 *local supplier quality*. The weights are calculated using Eq. (5), as given in Table 8.

The results show that the sum of the weights for the indicators #5, #7, and #8 is 1.245, 1.170, and 2.585, respectively. Therefore, indicator #8 *local supplier quality* has the highest impact on #9 *production process sophistication*.

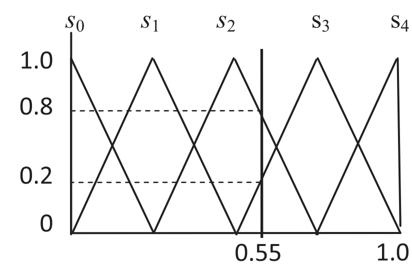

Fig. 4. Fuzzy sets for transforming the data into a belief structure.

In Table 9, the sums of the weights of the affecting indicators for all of the affected indicators are given. The weights given in this table are used to find out which indicators are more important for an affected indicator. For example, for #1 *domestic market size index*, #12 *ease of access to loans* is the most important indicator. Therefore, policymakers should focus on making loans more accessible,

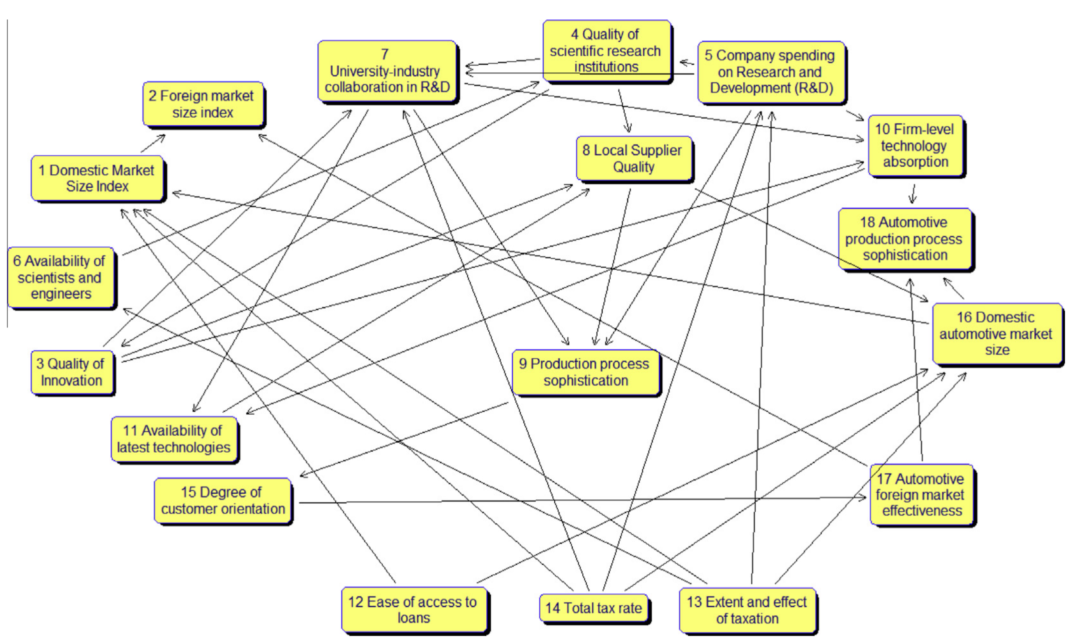

Fig. 3. Causal map of the system analyzed.

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Table 8
Weight related to indicator #9 *Production process sophistication*.

	w_{i0}^{95}	w_{i1}^{95}	w_{i2}^{95}	w_{i3}^{95}	w_{i4}^{95}	w_{i0}^{97}	w_{i1}^{97}	w_{i2}^{97}	w_{i3}^{97}	w_{i4}^{97}	w_{i0}^{98}	w_{i1}^{98}	w_{i2}^{98}	w_{i3}^{98}	w_{i4}^{98}
w_{0j}^{9l}	.333	0	0	0	0	.333	0	0	0	0	.333	0	0	0	0
w_{1j}^{9l}	0	.324	0	0	0	0	.399	0	0	0	0	.337	0	0	0
w_{2j}^{9l}	0	0	0	0	0	0	0	0.201	0	0	0	0	.622	.247	0
w_{3j}^{9l}	0	0	0	0.190	0	0	0	0	.297	0	0	0	0	.513	0
w_{4j}^{9l}	0	0	0	0.234	0.164	0	0	0	0	0	0	0	0	0	.603

to improve the domestic market size. A similar interpretation can be suggested to policymakers by using the weights in Table 9.

4.3. Validation of the results

Validation is a key issue in model-based research. In operations research, validation has been interpreted differently, depending on the epoch and context [13]. The validity of the models is an important concern, because decisions will be taken and resources will be committed as a result of the models built. There are two approaches to validity: (1) white box validity: the relationships between the factors of the model are correct; and (2) black box validity: the outputs produced by the model are expected given the inputs [18]. When the model employed is intended to be used for routine decision support, historical data and performance can be used to achieve black box validity. On the other hand, it is usual to rely on white box validation, in which the assumptions of the model and its parameters are examined critically when the model is built and used to explore options for the system configuration that do not exist. In this research, we employ both white box validity and black box validity, to ensure that the model that we developed serves its purpose and is valid to support the policymakers in their decisions. The white box validity is checked by an iterative model-building process that involves expert judgments, until the causal map of the system is obtained. Then, the black box validity is employed to check that the model's outputs perform as expected, given the defined inputs of historical data.

To validate the model output performance (i.e., the weights found in the previous section), we estimate the level of the indicators, based on the recent data for Turkey. We select Turkey in this analysis because, first, we develop the policy suggestions for Turkey in the next section, and second, we could only obtain Turkey's recent data, especially for the three automotive-related indicators.

The WEF report-based data (i.e., data related on indicators 1–15) are supplied by the WEF 2012–2013 Report [31]. Other data are collected from the REF's official webpage (http://Ref.sabanciuniv.edu/databases). The related data and their CBDs are given in Table 10.

Then, we employed the weights found in the previous section to estimate the level of the indicators. For example, the weights

Table 9
Sums of the weights of the affecting indicators.

ID #	Indicator	ID #	Affecting indicator	Sum of the weights
1	Domestic market size index	12	Ease of access to loans	1.907
		13	Extent and effect of taxation	1.239
		14	Total tax rate	1.576
		16	Domestic automotive market size	0.278
2	Foreign market size index	1	Domestic market size index	4.420
		17	Automotive foreign market effectiveness	0.580
3	Capacity of innovation	4	Quality of scientific research institutions	5.000
4	Quality of scientific research institutions	5	Company spending on R&D	2.644
		6	Availability of scientists and engineers	2.356
5	Company spending on R&D	13	Extent and effect of taxation	3.141
		14	Total tax rate	1.859
6	Availability of scientists and engineers	13	Extent and effect of taxation	5.000
7	University–industry collaboration in R&D	3	Capacity of innovation	0.746
		4	Quality of scientific research institutions	2.333
		5	Company spending on R&D	0.870
		14	Total tax rate	1.051
8	Local supplier quality	3	Capacity of innovation	2.589
		4	Quality of scientific research institutions	0.696
		11	Availability of latest technologies	1.716
9	Production process sophistication	5	Company spending on R&D	1.245
		7	University-industry collaboration in R&D	1.170
		8	Local supplier quality	2.585
10	Firm-level technology absorption	3	Capacity of innovation	1.505
		5	Company spending on R&D	2.019
		7	University-industry collaboration in R&D	1.476
11	Availability of latest technologies	7	University-industry collaboration in R&D	1.906
		10	Firm-level technology absorption	3.094
15	Degree of customer orientation	9	Production process sophistication	5.000
16	Domestic automotive market size	8	Local supplier quality	2.658
		12	Ease of access to loans	0.631
		13	Extent and effect of taxation	0.599
		14	Total tax rate	1.112
17	Automotive foreign market effectiveness	15	Degree of customer orientation	5.000
18	Automotive production process sophistication	10	Firm-level technology absorption	0.333
		16	Domestic automotive market size	1.487
		17	Automotive foreign market effectiveness	3.180

presented in Table 8 are used to estimate the level of indicator #9. For linguistic term level s_3, the following formula is used (note that the affecting indicators of #9 are #5, #7, and #8):

$$\gamma_{39}^{f} = \sum_{j=5,7,8}\sum_{l=0}^{5} w_{3j}^{9l}\gamma_{3j}^{r}$$

$$\gamma_{39}^{f} = 0.190 \cdot 0 + 0.297 \cdot 0 + 0.513 \cdot 0.47 = 0.24$$

where f and r are superscripts for estimated (forecasted) and real data, respectively. The actual and the estimated CBDs are presented in Table 10.

The mean absolute error (MAE) measure is used to compare real data and estimated data. Because all of the real data and the estimated data are CBDs, which can take on a value between 0 and 1, normalization is not required. MAE is calculated for an indicator as follows:

$$\mathrm{MAE}_k = \frac{1}{m+1}\sum_{i=0}^{m}|\gamma_{ik}^{r} - \gamma_{ik}^{f}|$$

For example, MAE for the first indicator is found as follows:

$$\begin{aligned}\mathrm{MAE}_1 &= \frac{1}{m+1}\sum_{i=0}^{m}|\gamma_{i1}^{r} - \gamma_{i1}^{f}| \\ &= \frac{(1-1)+(1-0.99)+(1-0.76)+(0.8-0.55)+(0-0.06)}{5} \\ &= 0.11\end{aligned}$$

MAE measures for all of the indicators are shown in Table 10. As a reference, suppose that we have no knowledge about the level of an indicator. Then, all of the linguistic term options can be considered to be possible. Therefore, the belief degrees for all linguistic term levels can be assumed to be $1/m$ [10]. For a specific case, the belief degrees are considered to be 0.2. This case will lead to a CBD of $\{(s_0,1.0),(s_1,0.8),(s_2,0.6),(s_3,0.4)(s_4,0.2)\}$. We find the MAE for each indicator, assuming that the estimates are made with no knowledge. The results are shown in the last column of Table 10.

Because the errors of the model estimates are much better than the errors of the no-knowledge cases (see the last two columns of Table 10), we can conclude that the model gives satisfactory results. Therefore, we comfortably use the model to develop policy suggestions in the next section.

4.4. Developing policy suggestions

The weights found in the previous stages are used for analyzing the current situation and possible different scenarios for the Turkish automotive industry. Turkey's current situation for the output indicators of the automotive industry are between very low and low $(\{(s_0,.46),(s_1,.54)\})$ in #16 *Domestic automotive market size*, between medium and high $(\{(s_2,.44),(s_3,.56)\})$ in #17 *Automotive foreign market effectiveness*, and between medium and high $(\{(s_2,.64),(s_3,.36)\})$ in #18 *Automotive production process sophistication* (see Table 8 and Fig. 5). Therefore, the first priority can be given to improve the domestic automotive market size. Because of the fact that the local supplier quality has the highest impact on this indicator (Fig. 5), the policymakers can focus on improving the quality of local suppliers of the automotive industry. To accomplish this goal, further improvements can be considered with regard to the capacity of innovation and the availability of the latest technologies. Another important criterion for the domestic automotive market is the total tax rate. Despite the fact that Turkey's tax rate (44.5%) is not high compared to other competing countries, if the policymakers decrease the taxes, then the positive effect of this change on the market size will help to improve the industry (see Fig. 5).

To reveal the specific effects of the different criteria, two scenarios are considered, based on Ulengin et al. [28]. Optimistic and pessimistic scenarios are designed to analyze the performance of the automotive industry in Turkey. In this scenario analysis, the input indicators, namely #3, #5, #7, #8, #11, and #13, are selected based on previous analysis of the industry [28]. The output indicators are performance indicators of the automotive industry, namely, indicators #16, #17, and #18.

In the optimistic scenario, each input indicator is set to the next upper linguistic term level. For example, the current level of #3 *innovation capacity* is $\{(s_1,.6),(s_2,.4)\}$, which means that it is between low (s_1) and medium (s_2). It is assumed that Turkey improves its innovation capacity to a high level (s_3) in the optimistic scenario. On the other hand, each input indicator drops to a previous lower level in the pessimistic scenario. For example, Turkey's innovation capacity is assumed to drop to a low level (s_1) in the pessimistic scenario. The levels of input indicators in the scenarios as well as the current levels are presented in Table 11.

Table 10
Data used for validation.

ID	Data	Normalized score	Turkey's real data: Cumulative belief degrees s_0	s_1	s_2	s_3	s_4	Estimated data: Cumulative belief degrees s_0	s_1	s_2	s_3	s_4	MAE – model estimates	MAE – NK
1	5.2	0.700	1.00	1.00	1.00	0.80	0.00	1.00	0.99	0.76	0.55	0.06	0.11	0.24
2	5.4	0.733	1.00	1.00	1.00	0.93	0.00	1.00	1.00	1.00	0.94	0.18	0.04	0.27
3	3.4	0.400	1.00	1.00	0.60	0.00	0.00	1.00	1.00	0.40	0.00	0.00	0.04	0.16
4	3.4	0.400	1.00	1.00	0.60	0.00	0.00	1.00	1.00	0.84	0.30	0.01	0.11	0.16
5	3.2	0.367	1.00	1.00	0.47	0.00	0.00	1.00	1.00	0.67	0.23	0.03	0.09	0.19
6	4.5	0.583	1.00	1.00	1.00	0.33	0.00	1.00	1.00	0.99	0.43	0.02	0.03	0.17
7	3.6	0.433	1.00	1.00	0.73	0.00	0.00	1.00	1.00	0.55	0.04	0.00	0.04	0.19
8	4.7	0.617	1.00	1.00	1.00	0.47	0.00	1.00	1.00	1.00	0.61	0.00	0.03	0.17
9	4.4	0.567	1.00	1.00	1.00	0.27	0.00	1.00	1.00	0.85	0.24	0.00	0.04	0.19
10	5.3	0.717	1.00	1.00	1.00	0.87	0.00	1.00	1.00	1.00	0.49	0.00	0.08	0.25
11	5.4	0.733	1.00	1.00	1.00	0.93	0.00	1.00	1.00	1.00	0.91	0.12	0.03	0.27
12	3.0	0.333	1.00	1.00	0.33	0.00	0.00							
13	3.0	0.333	1.00	1.00	0.33	0.00	0.00							
14	41.1	0.413	1.00	1.00	0.65	0.00	0.00							
15	5.4	0.733	1.00	1.00	1.00	0.93	0.00	1.00	1.00	1.00	0.51	0.00	0.09	0.27
16	104	0.160	1.00	0.64	0.00	0.00	0.00	1.00	0.74	0.56	0.30	0.05	0.20	0.27
17	0.53	0.588	1.00	1.00	1.00	0.35	0.00	1.00	0.99	0.96	0.20	0.00	0.04	0.17
18	1.53	0.509	1.00	1.00	1.00	0.04	0.00	1.00	0.86	0.60	0.27	0.02	0.16	0.23
											Average MAE		0.07	0.21

MAE: Mean Absolute Error, NK: no knowledge.

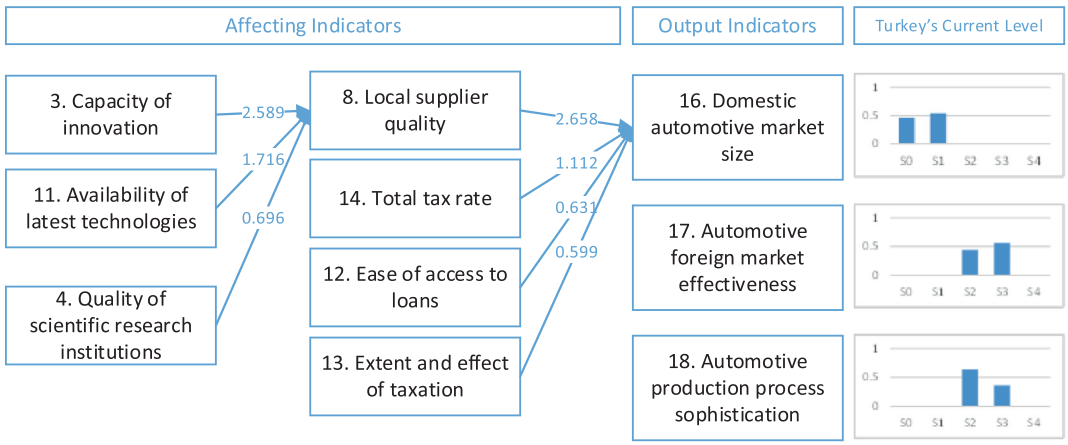

Fig. 5. Important criteria for the Turkish automotive industry.

The resulting levels of the output indicators are given in the last three rows of Table 11 and in Fig. 6. The results are consistent with the expectations because of the possibility of output level increases in the optimistic scenario, whereas there is a possibility of output level decreases in the pessimistic scenario.

According to the results, if Turkey shows the improvement defined in the optimistic scenario, #16 *Domestic automotive market size* will be *high* (s_3), with a value of .72, and *very high* (s_4), with a value of .28, in terms of the belief degrees; #17 *Automotive foreign market effectiveness* will be *very high* (s_4), with a value of .84 in terms of the belief degree; and #18 *Automotive production process sophistication* will be *very high* (s_4), with a value of .82 in terms of the belief degree. However, when the situation worsens (i.e., the pessimistic scenario), #16 *Domestic automotive market size* will decrease to *very low*, with a value of .39, and *low* (s_1), with a value of .41, in terms of the belief degrees. The level of the #17 *Automotive foreign market effectiveness* will become very uncertain, but the

Table 11
Level of the input and output indicators in the scenarios.

ID #	Type	Indicators	Current level	Level in optimistic scenario	Level in pessimistic scenario
3	Input	Innovation capacity	$\{(s_1,.6),(s_2,.4)\}$	$\{(s_3,1.0)\}$	$\{(s_1,1.0)\}$
5	Input	Company spending on R&D	$\{(s_1,.67),(s_2,.33)\}$	$\{(s_3,1.0)\}$	$\{(s_1,1.0)\}$
7	Input	University-industry collaboration in R&D	$\{(s_1,.4),(s_2,.6)\}$	$\{(s_3,1.0)\}$	$\{(s_1,1.0)\}$
8	Input	Local supplier quality	$\{(s_2,.6),(s_3,.4)\}$	$\{(s_4,1.0)\}$	$\{(s_2,1.0)\}$
11	Input	Availability of latest technologies	$\{(s_3,1.0)\}$	$\{(s_4,1.0)\}$	$\{(s_2,1.0)\}$
12	Input	Ease of access to loans	$\{(s_1,.93),(s_2,.07)\}$	$\{(s_3,1.0)\}$	$\{(s_1,1.0)\}$
13	Input	Extent and effect of taxation	$\{(s_1,.73),(s_2,.27)\}$	$\{(s_3,1.0)\}$	$\{(s_1,1.0)\}$
16	Output	Domestic automotive market size	$\{(s_0,.46),(s_1,.54)\}$	$\{(s_3,.72),(s_4,.28)\}$	$\{(s_0,.39),(s_1,.41),(s_2,.17),(s_4,.03)\}$
17	Output	Automotive foreign market effectiveness	$\{(s_2,.44),(s_3,.56)\}$	$\{(s_1,.01),(s_2,.12),(s_3,.03),(s_4,.84)\}$	$\{(s_0,.19),(s_1,.12),(s_2,.52),(s_3,.18)\}$
18	Output	Automotive production process sophistication	$\{(s_2,.64),(s_3,.36)\}$	$\{(s_0,.01),(s_1,.03),(s_2,.12),(s_3,.03),(s_4,.82)\}$	$\{(s_0,.34),(s_1,.19),(s_2,.28),(s_3,.17),(s_4,.02)\}$

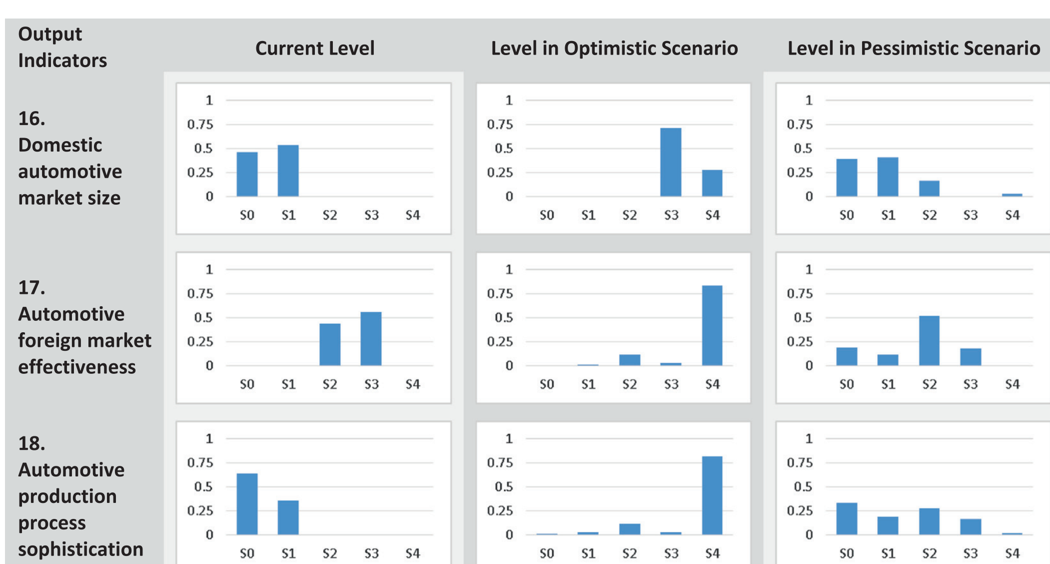

Fig. 6. Level of output indicators in the scenarios.

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highest belief is calculated for *medium* (s_2), with a value of 0.52. Similarly, the pessimistic scenario made the #18 *Automotive production process sophistication* very uncertain, because the possibility is distributed to very low, low, medium, and high, almost evenly.

5. Conclusions

In this study, a three-stage methodology is proposed to analyze the competitiveness of the automotive industry in Turkey. In the second stage of the methodology, a CBD approach is used to quantify the relations among the variables in the automotive industry. The results of the CBD approach are then used to make a scenario analysis of the Turkish automotive industry.

One of the novel contributions of this study is the use of the CBD approach to quantify the relations among the variables in a system. The method can be applied to any data, as long as the data are transformed into belief structures. This property can be useful when different types of data are available in a single problem, such as expert judgments, numerical values, and linguistic expressions. The applicability of the problem is justified by an illustrative example as well as by the automotive industry application.

Another important merit of the CBD approach is that what-if or scenario analysis can be conducted using linguistic terms. Most of the data-driven systems analysis approaches require exact data to make what-if analyses. However, policymakers can find it difficult to generate exact data for such a type of analysis. Therefore, using linguistic terms will facilitate the analysis by making it easier and understandable for policymakers.

The current study uses only hard data, modeled through expert opinions, to find the strength of the relations among the indicators. It could be more reliable if the experts' judgments were integrated into the hard data, when making an analysis for a specific country or industry. The CBD approach can effectively handle a situation in which the information comes from different sources.

Although the proposed methodology provided satisfactory outputs, its accuracy can be improved further. For example, in its current state, the importance weights are calculated by using a regression-based method, which assumes linear relations. However, artificial intelligence methods, such as artificial neural networks (ANNs), can be used, to omit the linearity assumption. In fact, ANNs form a class of nonparametric models that acquire knowledge under the conditions of noise and uncertainty. In doing so, they perform generalization and abstraction, and they create their own knowledge by self-organization [25].

Furthermore, user-friendly software can be developed to facilitate the calculations of the proposed methodology. In this way, the widespread usefulness and applicability of the proposed methodology to other industries as well as to research domains other than competitiveness can be increased.

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