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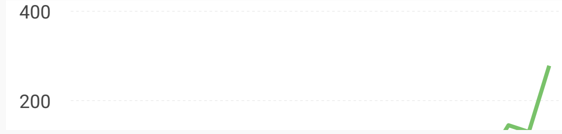

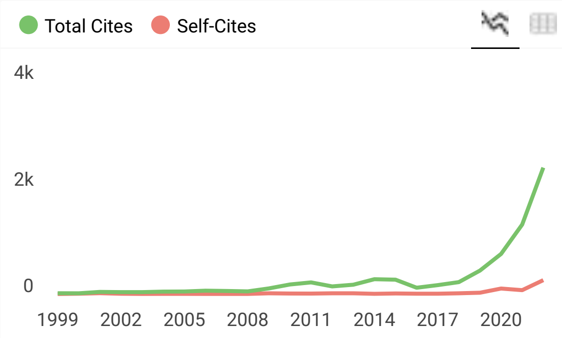

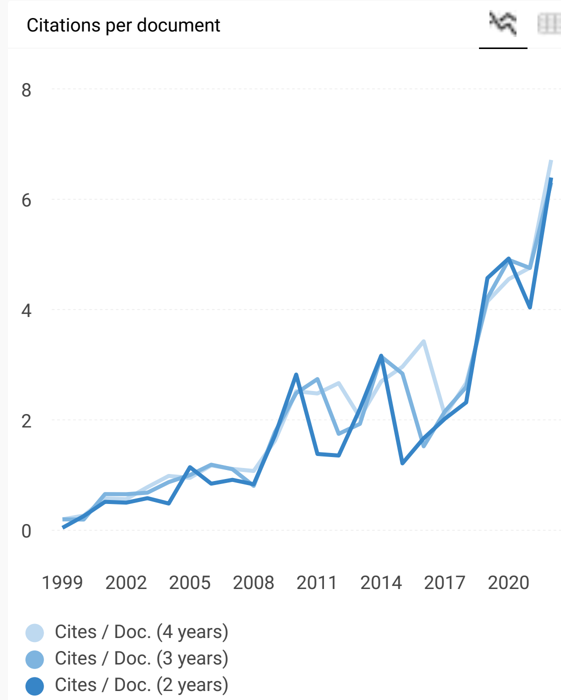

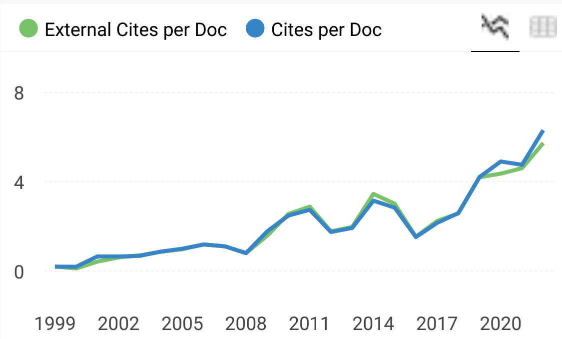

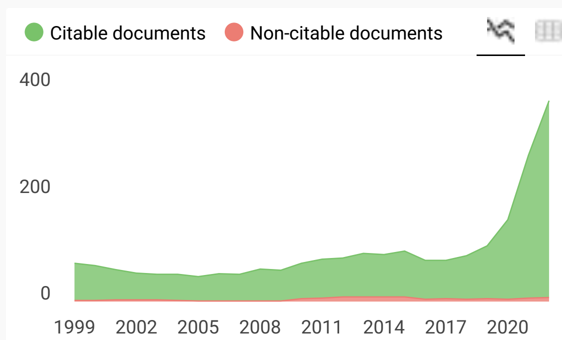

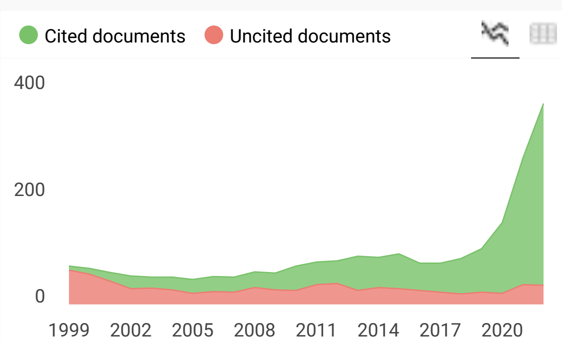

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Analysis of the innovation capacity of Mexican regions with the multiple criteria hierarchy process

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ABSTRACT

This study attempts to use multicriteria decision aiding (MCDA) tools to analyse the innovation capacity of 32 regions in Mexico. In today's competitive world, innovation in science and technology is the key to the growth and productivity of the regions. Understanding the current state of innovation capacity and identifying the factors that influence said capacity allows the government to make region-specific policies for future growth and development. However, measuring such a complex concept involves a large number of criteria, and to understand the impact of a region's innovation capacity under a subset of criteria or with respect to high-level views it is necessary to gain in-depth insight for future policy design. To address this issue, we adopt the multicriteria hierarchy process (MCHP), which allows the decision-maker to express preferences of sub- group criteria and individual analysis by using subsets of criteria and different dimensions of the problem. Further, with the aim of managing the weighting of criteria and preference aggregation within the MCHP framework, we employ the hierarchical version of the deck of cards method for weight definition, the hierarchical ELECTRE III to aggregate preferences, and the distillation procedure to exploit the preference model. Using this methodological framework, the innovation capacity of 32 regions in Mexico is analysed under 52 decision criteria.

1. Introduction

From an economic perspective, knowledge transformed into innovation should (in theory) have an impact on the development of regions and countries. Knowledge-based economies have flourished in different parts of the world, and the production processes that give rise to this phenomenon have been extensively studied through different approaches. Some researchers focus on the performance aspect of innovation (input/output efficiency performance) (e.g. [1–4]), while others tend to study the conditions and capabilities of regions and countries to generate innovation (e.g. [5–9]).

In a world where competition is rapidly increasing and Science, Technology & Innovation (STI) are the most decisive players and countries need to shape their policies accordingly. Advances in science and technology and innovation-based strategies have become the basic elements of increased productivity and competition at both country and company levels [10].

The results of the study on Science, Technology & Innovation Policy (STIP) by Chaurasia and Bhikajee [11] allow for recommendations on incorporating "entrepreneurship" in STIP regarding the government's involvement in innovations and transparency, and the incorporation of an entrepreneurial curriculum. In [12] a descriptive statistics analysis under the innovation policy framework is carried out. It is based on the industry 4.0 and sustainability development transition. The study also conducts a comparative policy analysis between China and Taiwan. Ozkaya et al. [10] developed a comparison framework by taking advantage of existing STI policy indices and comparing countries using these indicators with different Multiple Criteria Decision-Making (MCDM) methods.

Investment in human capital and skills development is known to have a positive relationship with economic growth in lower middle-income countries. However, technology adoption and innovation have a different linkage within regions across lower middle-income countries [13].

The European Commission published the 2018 Industrial R&D Investment Scoreboard. It shows that the biggest difference that separates developed countries from developing countries is the knowledge gap between them [14].

The regional STI indicator comparisons can be considered an important guide for governments in policy formulation on economy,

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welfare, and development issues. The importance of designing STI indicators and frameworks in regional and international comparisons should be a priority for governments to form national and international policies [15,16].

In this regard, an emphasis has been made on identifying the appropriate innovation criteria for describing the characteristics that endow the regions with the capabilities required for generating economic growth through innovation activities. Through these criteria, some studies aim to create composite indicators that classify and rank regions based on their innovation capacities.

In Mexico, the Scientific and Technological Advisory Forum gathered some indicators that measure the Science, Technology, and Innovation (STI) characteristics of regions [17]. Such efforts produced indicator systems, which were used with principle components to obtain weights that allowed for differentiation among the Mexican states and revealed the state of innovation capabilities and capacities of regions. Furthermore, this information was then applied to cluster analysis to identify internal behavioural patterns of the states with regard to STI capacities and capabilities.

This paper aims to utilize the multiple criteria hierarchy process to analyse the innovation capacity of regions in Mexico, comparing them with respect to 52 STI indicators, as an alternative approach. Due to the characteristics of the innovation capacity problem regarding the number of indices and the heterogeneity of their values, it seems appropriate to approach it as an MCDM problem. The number of dimensions and indices to describe STI characteristics implies a hierarchy problem approach. In this regard, addressing it as a hierarchy of criteria would be helpful for the analysis of the comprehensive problem and the inherent dimensions of the STI indicators to describe the innovation capacity of regions. To the best of our knowledge, this is the first time an MCDA based on the hierarchy approach has been applied to analyse the innovation capabilities of region.

The main contributions of the current research are as follows:

– The assessment of the performance of innovation capacity in different regions in Mexico
– Identifying those with the highest innovation capacity through their different dimensions among the 32 regions in Mexico.
– The development of two computational tools, one that systematizes the Electre III and the distillation method in the MCHP context and other that systematizes the SRF method.

The paper is organized as follows. The literature review is presented in Section 2, describing multiple criteria hierarchy methods. In Section 3, the multiple criteria decision aid process and the MCHP are described regarding the ELECTRE III, distillation and SRF method, pointing out the hierarchical structure approach. The innovation capacity of Mexican regions is addressed with the MCHP in Section 4, and Section 5 describes conclusions and future research.

2. Literature review on multiple criteria hierarchy methods

Multiple Criteria Decision Aiding (MCDA) deals with various problem statements to support the Decision-Maker (DM): description, choice, ranking, and sorting (see [18], for more details). Discrete problems involve the analysis of a finite discrete set of alternatives, $A = \{a_1, \ldots, a_i, \ldots, a_m\}$, where each alternative is assessed through a finite set of criteria $G = \{g_1, \ldots, g_j, \ldots, g_n\}$ (see [19]).

In MCDA, four approaches have been developed with many methods for each approach: full aggregation; outranking; goal, aspiration or reference level; and the non-classical MCDM approach [20].

A series of methods based on the Multiple Criteria Hierarchy Process (MCHP) have been developed and will be described as follows. In AHP [21] a methodology is proposed to structure the problem in a hierarchy of criteria to analyse it at different levels of criteria. In this method, the analyst constructs a hierarchy modelling general criteria (subcriteria) to achieve the goal (comprehensive problem). The MCHP helps to understand the problem through (hierarchies) subproblems that need to be clear and straightforward in their description.

Corrente et al. [22] proposed an MCHP framework to analyse preference relations from the subset of criteria into different levels of a hierarchy. It applies Robust Ordinal Regression (ROR) to find all sets of parameters reflecting the DM's preference model (see [23], for further details). The method generates the necessary and possible preference relations related to subsets of criteria at different levels of the hierarchy, which hold for all compatible sets of parameters or for at least one compatible set of parameters.

Later, the hierarchical version of outranking methods, such as the ELECTRE and PROMETHEE methods, are adapted by Corrente et al. [24]. The extension of these outranking methods makes it possible to obtain the partial preference relation with respect to subcriteria at different levels of the hierarchy. In this method, authors assert that the hierarchy of criteria decomposes and simplifies the preference elicitation concerning pairwise comparisons of criteria with respect to relative importance.

The ELECTRE-III-H method is proposed by Del Vasto-Terrientes et al. [25]. It is an extension of the ELECTRE-III method to deal with a hierarchy of criteria. As an outranking method, the ELECTRE-III-H method is based on concordance and discordance tests. The exploitation of this outranking relation generates a partial pre-order, establishing an indifference, preference or incomparable relation for each pair of alternatives at different levels of the hierarchy. The main difference compared with the proposal by Corrente et al. [24] is that [25] proposed a new procedure to build outranking relations from a set of partial pre-orders along with a mechanism for propagating these pre-orders upwards in the hierarchy.

Another extended version of ELECTRE III was proposed by Corrente et al. [26]. The method involved in MCHP an imprecise elicitation of criteria weights with an extended version of the SRF method. Moreover, the Stochastic Multiobjective Acceptability Analysis (SMAA) is adapted to draw robust conclusions in terms of rankings and preference relations at each level of the hierarchy of criteria. The hierarchical assessments of the performances of the alternatives in this method enable the interaction of criteria regarding the mutual-weakening, mutual-strengthening and antagonistic effect.

Angilella et al. [27] developed an extended version of Choquet integral for MCHP (hierarchical-SMAA-Choquet integral). The method implements ROR and SMAA to the hierarchal Choquet integral preference model. The input is indirect preference information provided by the Decision-Maker and takes the form of pairwise comparisons of criteria with respect to their importance and pairwise preference comparisons of some pairs of alternatives with respect to some criteria. The method includes a disaggregation and robust hierarchical method. Later, the proposal was applied for the evaluation of sustainable rural development through composite indices related to economic, social, and environmental aspects [28].

De Matteis et al. [29] studied the Italian co-payment healthcare system. The authors applied the hierarchical-SMAA-Choquet integral method proposed in [27]. The application makes it possible to estimate an index of inequality of opportunities in public health, in absence of information about the real health care needs of people. The study measures the inequality, mainly determined by the differences between regional co-payment prices, and creates an index for each region that allows for classification among them.

Bernal et al. [30] applied the MCHP method to a portfolio selection problem involving evaluation and selection of assets from the stock exchange. In fact, they adopted the MHCP method proposed by Corrente et al. [24] to analyse the assets regarding the investor's preferences and establish a portfolio.

In sorting problems, it seems the first method extended to an MCHP is the one proposed by Del Vasto-Terrientes et al. [31]. The ELECTRE-TRI-B-H method handles assignments of alternatives to predefined

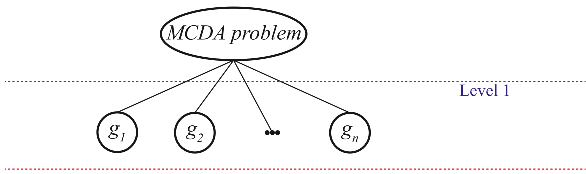

Fig. 1. Assessment of criteria considered at the same level.

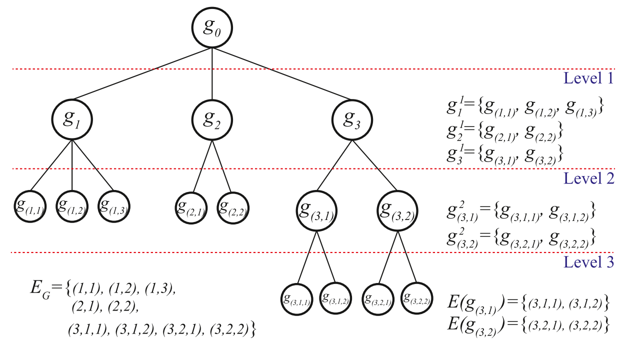

Fig. 2. Representation of the hierarchy of criteria for a MCHP.

categories at several levels of the hierarchy. The method compares the evaluations of alternatives with the profile limits separating the categories. This method is applied to the integration of a recommender system (GoEno-Tu) of touristic activities related to wine. The aim of this application in the hierarchy is to allow intermediate criteria to correspond to different aspects of the recommendation procedure, such as content, context or cost.

The UTADIS (UTilités Additives DIScriminantes) and UTADIS[GMS] are well-known sorting methods that use value function models. Both methods are extended by Corrente et al. [32] to infer decision models from sorting decision examples, using a formal MCHP framework and then being applied to sorting banks into five predefined categories.

The analytical hierarchy process (AHP), proposed by Saaty [21], is quite different from current MCHP approach because AHP proposes global priorities of alternatives concerning only the comprehensive problem. However, in MCHP, the hierarchy allows the generation of a ranking (or sorting) of alternatives in any node of the hierarchy.

3. The multiple criteria decision aid process

For the classical problem, it is mostly assumed that the evaluation of criteria should be performed at the same level (see Fig. 1). When the problem is approached across the same level for all criteria, it focuses on just one view, a global problem. It means we cannot identify how some subsets of criteria are impacting the alternatives regarding criteria performance.

3.1. The multiple criteria hierarchy process

A hierarchical structure of criteria corresponds to a group of subsets of elementary criteria in macrocriteria. That means each macrocriterion represents a part of the problem from one point of view, without regard for the rest of the family of criteria defined for the comprehensive problem. This way, the problem can be partitioned into smaller problems and analysed using more focused views, starting from focused views and then scaling up to a more comprehensive view.

Considering a hierarchical instead of a flat structure of criteria allows the decomposition of a complex decision problem into smaller problems involving fewer criteria [22]. Corrente et al. [22] introduce the Multiple Criteria Hierarchy Process (MCHP) approach. The basic idea of MCHP relies on considering preference relations at each node (macro-criterion) of the hierarchy tree of criteria.

To describe the hierarchical version of the outranking Electre III method, we follow the notation used in [28].

- G is the set of criteria at all considered levels in the hierarchy.
- G_0 is the root criterion.
- l_G is the set of indices of the criteria in G.
- $E_G \subseteq l_G$ is the set of indices of elementary criteria.
- g_r the generic criterion, different from non-root (where r is a vector with length equal to the level of the criterion).
- $g_{(r,1)}, \dots, g_{(r,n(r))}$ the subcriteria of criterion g_r. They are located at the immediate level belonging to g_r.
- $E(g_r)$ the set of indices of all the elementary criteria belonging to g_r.
- $E(F)$ the set of indices of the elementary criteria belonging to at least one criterion in the subfamily $F \subseteq G$ (that is, $E(F) = \bigcup_{g_r \in F} E(g_r)$).
- G_r^l is the set of subcriteria of g_r located at level l in the hierarchy (belonging to g_r).
- L is the number of levels of the hierarchy, $l = 1, \dots, L$.

Fig. 2 represents a graphical schema of a multiple criteria hierarchical process (MCHP). A multiple criteria decision problem is defined with a set of elementary criteria in a hierarchical structure. The deepest level of the hierarchy (Level 3) contains four elementary criteria represented by indices $(3,1,1), (3,1,2), (3,2,1)$ and $(3,2,2)$, where $E(g_{(3,1)}) = \{(3,1,1),(3,1,2)\}$ and $E(g_{(3,2)}) = \{(3,2,1),(3,2,2)\}$). Level 2 contains five elementary criteria represented by indices $(1,1), (1,2), (1.3)$, $(2,1)$ and $(2,2)$. We can see that elementary criteria are placed not only at different levels of the hierarchy, but grouped in different sets of $E(g_r)$. This non-flat structure allows us to assess the elementary criteria at different levels. It enables the decomposition of the problem (splitting) and its analysis through subproblems. The approach provides a structured procedure to observe the behaviour of the problem in different approaches (e.g., the solution of the subproblem on the criterion $g_{(3,1)}$ from Level 2 can be different from the subproblem of the criterion g_3 from Level 1). We can have a different approach to the problem, focusing on specific parts, or more comprehensive information. This is possible when a hierarchy of the family of criteria is presented.

3.1.1. The hierarchical Electre III method

The adapted version of the hierarchical Electre III ($h-$Electre III) was first introduced by Corrente et al. [24]. For each elementary criterion g_t, $t \in E_g$, the following thresholds should be specified: indifference q_t, preference p_t, and veto v_t threshold. They help to construct three binary relations: aS_tb is an outranking relation that means "a is at least as good as b with respect to criterion g_t"; aQ_tb is the weak preference and; aP_tb is the strict preference.

1. The elementary concordance index, for each elementary criterion g_t,

$$c_t(a,b) = \begin{cases} 1, & \text{if} \quad g_t(b) - g_t(a) \leqslant q_t, (aS_tb) \\ \dfrac{p_t - \left(g_t(b) - g_t(a)\right)}{p_t - q_t} & \text{if} \quad q_t < g_t(b) - g_t(a) < p_t, (aQ_tb) \\ 0, & \text{if} \quad g_t(b) - g_t(a) \geqslant p_t, (bP_ta). \end{cases} \tag{1}$$

2. The elementary discordance index, for each elementary criterion g_t,

$$d_t(a,b) = \begin{cases} 1, & \text{if} \quad g_t(b) - g_t(a) \geqslant v_t, \\ \dfrac{\left(g_t(b) - g_t(a)\right) - p_t}{v_t - p_t} & \text{if} \quad p_t < g_t(b) - g_t(a) < v_t, \\ 0, & \text{if} \quad g_t(b) - g_t(a) \leqslant p_t. \end{cases} \tag{2}$$

3. The partial concordance index, for each non-elementary criterion g_r,

$$C_r(a,b) = \frac{\sum_{t \in E(g_r)} w_t c_t(a,b)}{\sum_{t \in E(g_r)} w_t}. \tag{3}$$

4. The partial credibility index, for each non-elementary criterion g_r,

$$\sigma_r(a,b) = \begin{cases} C_r(a,b) \times \prod_{g_t \in E(g_r)} \dfrac{1 - d_t(a,b)}{1 - C_r(a,b)} & \text{if} \quad d_t(a,b) > C_r(a,b) \\ C_r(a,b), & \text{if} \quad otherwise \end{cases}, \tag{4}$$

3.1.2. The distillation process at MCHP

The distillation-ranking algorithm is used in the exploitation procedure of the fuzzy outranking relation. It is based on the degrees of credibility of each action to get a final partial preorder, resulting from the intersection of two complete preorders [33].

The algorithm for ranking alternatives is based on two distillation procedures, descending and ascending distillation. Each procedure locates the best alternative in the first position and the worst in the last. Descending distillation ranks alternatives from top to bottom while ascending distillation ranks alternatives from bottom to top.

The distillation procedure uses the fuzzy relation matrix $[\sigma(a,b)]$ generated by an outranking approach to rank the best alternatives at the top of the ranking and the worst at the bottom. The ranking is generated by establishing the cut level and distillation threshold to generate a crisp outranking relation.

The crisp outranking relation is calculated by using the $\lambda_k - power$ and $\lambda_k - weakness$ of a, where $\lambda_k - power$ indicates the number of alternatives outranked by a and $\lambda_k - weakness$ represents the number of alternatives that outrank a [33]. The $\lambda_k - qualification$ of a can be interpreted as the balance between $\lambda_k - power$ and $\lambda_k - weakness$ and used to identify the best and the worst alternative at the current distillation stage. The alternative with a maximum qualification is selected for descending distillation or the minimum qualification for ascending distillation. When descending and ascending distillation are finished, two complete preorders are obtained.

Finally, a complete or partial preorder is obtained from the intersection of the complete preorders generated in the descending and ascending distillation. A technical description of the distillation-ranking algorithm is explained in Appendix A. For further details see [33].

For the multiple criteria hierarchical process (MCHP), a fuzzy outranking relation is obtained for the comprehensive problem and for each macro criterion in Level 1 to Level $L-1$. In this sense, the ELECTRE-III constructs the fuzzy outranking relation and the distillation-ranking algorithm generates the final preorder in each macro criterion.

Fig. 3 illustrates the schematic process of the aggregation and exploitation of alternatives in a hierarchical process. From bottom to top, a fuzzy outranking relation and final preorder are generated in each node of the hierarchy. In Level 1, the macrocriterion g_1 uses the elementary criteria $g_{(1,1)}$ and $g_{(1,2)}$ to construct the fuzzy outranking relation with ELECTRE-III and generate the final preorder with the distillation procedure. The macrocriterion g_2 uses the elementary criteria $g_{(2,1)}$ and $g_{(2,2)}$. Finally, for the comprehensive problem, at the root of the tree, the set of elementary criteria $\{g_{(1,1)}, g_{(1,2)}, g_{(2,1)}, g_{(2,2)}\}$ is used. It can be observed that more elementary criteria are taken into account as the node moves up the hierarchy. A different process is found in the proposal by Del Vasto-Terrientes et al. [25] for the aggregation at intermediate levels of the hierarchical tree. Authors proposed a different calculation of the partial concordance and discordance indices by using the partial preorders generated at lower levels.

3.2. Hierarchical deck of cards method

The deck of cards playing procedure was proposed to support the definition of weight parameters by Simos [34]. Later, [35] revised and improved the Simos' procedure, and re-named it as Simos' Revised Procedure. The authors also developed the software called Simos–Roy–Figueira (SRF) with this improved version of the procedure. In the rest of the text the term SRF will be used to refer Simos' Revised Procedure.

Figueira and Roy [35] state that this procedure is significant from a DM's preference point of view. One advantage of the SRF is the intuitive way to express preference information about the importance of criteria through a deck of cards playing procedure. The first stage of the method is for collecting preference information. In the second stage, the deck of cards method determines the weights. A brief description is presented in Appendix B.1 and illustrative data are shown in Table B.5 to explain the procedure.

An extended version of the SRF was proposed by Corrente et al. [36] to support the definition of the weight in a hierarchy of criteria. In the current innovation capacity problem, it seems that it is the first time the extended SRF has been applied. We will use the term hierarchical deck of cards method (HDCM) to refer to this extended version.

Next, we will describe the two stages of the HDCM. For further details on the method, see [36]. In Stage 1, SRF is applied to any set of subcriteria at each level of the hierarchy. At this stage, a set of weights are generated for each level. The weights of each level are not related to the weight sets of other levels. In Stage 2, the weight sets are integrated from all levels in a hierarchical relationship. The steps in each stage are listed below.

Stage 1: *Apply SRF to any set of subcriteria at each level of the hierarchy*
In stage 1, six steps for applying the SRF to a hierarchy are explained below.

Step 1 Begin at the top of the hierarchy (comprehensive level), $l = 0$
Step 2 Apply SRF to the immediate subcriteria G_r^l from node g_r
Step 3 Assign the output weights to corresponding subcriteria
Step 4 Go to the next level (lower level), $l = l + 1$
Step 5 For any node g_r on l, implement Steps 2 and 3 in the immediate subcriteria G_r^l
Step 6 Repeat Steps 4 and 5 while $l < L$

Each subset of weights corresponds to one set of subcriteria in the hierarchy. For each macrocriterion g_r the corresponding weights of immediate subcriteria $\sum_{j=1}^{n(r)} w_{(r,j)} = 1$. Because the sum of weights is 1 in each subcriteria set (node), we say that the weights are unrelated to the other subcriteria in the hierarchy. This is because SRF is applied individually to any g_r, such that the sum of all elementary criteria weights is higher than one ($\sum_{t \in E_G} w_t > 1$).

Stage 2: *Integrate the subcriteria weights in a hierarchical relationship to the other subcriteria at all levels of the hierarchy*
The integrating process of HDCM normalizes the weights generated by the SRF in each node. In this sense, we call them SRF weights (w^{SRF}) when they are first generated by SRF, and HDCM weights (w^{HDCM}) when they are normalized for the hierarchy. To integrate all weights for

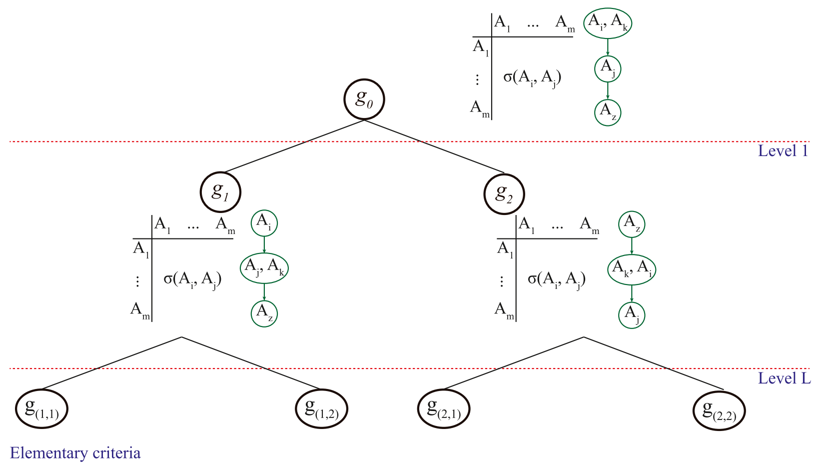

Fig. 3. Aggregation and exploitation of alternatives in the MCHP.

the Multiple Hierarchy Process (MCHP), we normalize the elementary criteria weights using the corresponding importance weights from top to bottom.

Step 1: Weights at Level 1, the computed weights by SRF on Level 1 remain the same in HDCM

Step 2: Weights at lower levels ($l > 1$), each SRF weight $w_{(r,j)}$ (corresponding subcriterion $g_{(r,j)}$) is multiplied by the immediate upper HDCM weight (corresponding macrocriterion g_r).
For non-elementary criteria $w_{(r,j)}^{HDCM} = w_{(r,j)}^{SRF} * w_r^{HDCM}, \forall g_{(r,j)} \in g_r, j = 1, \dots, n(r)$. For elementary criteria $w_{(t,j)}^{HDCM} = w_{(t,j)}^{SRF} * w_r^{HDCM}, \forall g_t \in g_r, t \in E(g_r)$. where
$w_{(r,j)}$ is the weight of the non-elementary criteria of $g_{(r,j)}$
$w_{(t,j)}$ is the weight of the elementary criteria, $t \in E(g_r)$

Step 3: Repeat step 2 until there are no more sets of criteria left in the level $(g_{r+1}, \dots, g_m)$.

Step 4: If there are more levels in the hierarchy, go to the next level $(l = l + 1)$ and repeat Step 2

Stage 2 of the HDCM normalizes the elementary criteria to get $\sum_{t \in E_G} w_t = 1$, relating the weights in the hierarchy. In Stage 2, each SRF weight is converted into an HDCM weight. For the MCHP, the final weights obtained from HDCM are used to construct the aggregated model in the aggregation stage.

3.3. *The* Electre *family methods for innovation capacity*

This section is dedicated to explaining the importance of the implementation of the Electre III to deal with the Innovation capacity problem. The science, technology, and innovation (STI) criteria have heterogeneous scales and some of them are characterized by imperfections, thus making it difficult to impose crisp decision rules on the scales of the criteria to describe the innovation capacity of regions. The fuzzy outranking relations of the electre methods provide the means to address this difficulty.

The Electre III family methods are able to handle qualitative performance scales of criteria [37]. The innovation capacity studied here takes into account some elementary criteria that represent in some way the qualitative impact on the innovation. The macro criteria and elementary criteria are listed in Appendix C, Table C.6. Some of them are quantitative by their very nature; however, they represent qualitative impact. The macro-criterion Entrepreneurial Infrastructure (g6) includes the elementary criteria *RENIECYT Members per/10 000 Economic Units* (6,2). The macro-criterion Institutional Component (g8) regards the elementary criterion *Normative framework for STI Planning* (8,1). The macro-criterion Gender in STI (g9) includes some criteria with a qualitative impact on innovation capacity; *CONACYT Scholarships by Gender* (9,1), *STI Enrolment by Gender* (9,2), *Social Sciences Enrolment by Gender* (9,3), *Gender Rate for NRS Researchers* (9,4), *Rate of Women Legislators for Science and Technology Commissions* (9,5). All criteria are processed as qualitative criteria, even through some are quantitative by their very nature.

Regarding the criteria mentioned above, the use of the electre methods seems to be convenient due to the procedures for exploitation of binary outranking relations that allow the formulation of recommendations in an interval format [38]. This supports the comparison of regions particularly when it is difficult to derive exact innovation capacity assessments. Further, [38] mentioned other techniques for providing recommendations in an interval format. They usually assume interval inputs about the uncertainty in the parameters of the decision model and the data, whereas in electre methods such recommendations are derived directly from simpler (crisp) information and explicitly represent the imperfect knowledge that characterizes the decision model.

The multicriteria aggregation procedure of electre is conceived such that they do not allow for compensation of performances among criteria [37]. The innovation capacity of Mexican regions can be analysed with Electre III, in case the expert explicitly considers cases where the innovation capacity deteriorates significantly due to poor performance on specific critical criteria.

The use of electre methods is particularly pertinent in contexts where at least one of the following features is present [37]: (1) the presence of qualitative scales for some criteria; (2) the presence of heterogeneous scales; (3) the need to avoid systematic compensatory effects; (4) the need to take into account the imperfect knowledge of data and some arbitrariness when building criteria; and (5) the need to take into account the reasons for and the reasons against an outranking. For the innovation capacity problem, at least the characteristics of 1, 2 and 4 are present.

In addition to these described characteristics, the hierarchical version of Electre III and SRF are adequate to support the DM with the innovation capacity problem. In comparison with the Electre-III-H method by Del Vasto-Terrientes et al. [25], the behaviour and the result of Electre III is well known. Further, the former builds outranking relations from a set of partial pre-orders from lowers levels. Electre III builds outranking relations from the elementary criteria in the usual way. This process directly uses the values of criteria instead of other processed information.

Whilst AHP is a well-known hierarchical method, comparing alternatives with respect to each criterion demands a huge cognitive effort from the decision-maker, when the number of alternatives is more than 9. As the innovation capacity problem involves a large number of alternatives and criteria, AHP is not suitable to address this issue.

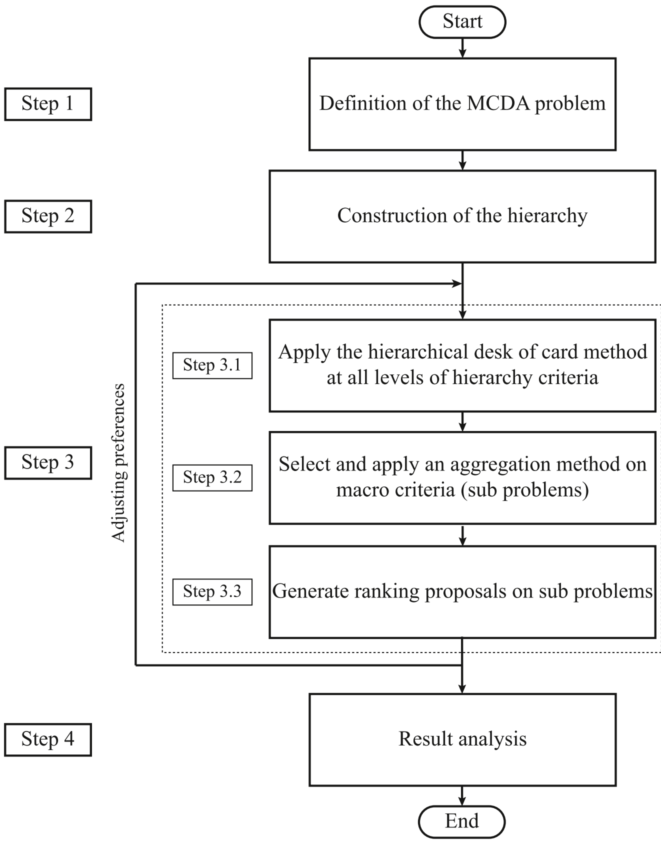

Fig. 4. Flow chart of the research methodology with MCDA for the innovation capacity problem.

3.4. Methodology to address the innovation capacity

The applied methodology is illustrated in the flow chart of Fig. 4. In Step 1, we define a multiple criteria ranking problem. Once the problem is defined, Step 2 focuses on the construction of the hierarchy.

Step 3 consists in aggregating the decision-maker's preference and generating the ranking of subgroups of criteria. The selected hierarchical method is the hierarchical version of ELECTRE-III (see Section 3.1.1). The decision-maker is supported by the SRF method to aggregate the definition of the weights (see Section 3.2). The main motivation for using ELECTRE III is to support and deal with different scales in the data, and to have the opportunity to express preferences in indifferent and preference thresholds. SRF is adequate to support the weight definition in a hierarchical structure. The computational tools Hierarchical-ELECTREIII, distillation-ranking algorithm, and Simos' Revised Procedure are available at https://github.com/paac80.

Finally, in Step 4, the result analysis describes the position of alternatives at a comprehensive level, but points out each alternative's achieved position in each defined subproblem. It is worth mentioning that Step 3.2 can be replaced by a different approach (e.g., full aggregation, outranking, reference level, rule decision).

4. Case study: Innovation capacity

The case study addresses the science, technology, and innovation (STI) capacities of Mexican states. The problem's intrinsic dimensions can be analysed by MCHP to generate a ranking of regions by dimension. The STI capacities present different STI indices, and these are grouped into available subsets to evaluate the dimensions of the structure. Hence, these characteristics make the proposed methodology an appropriate way of dealing with this multiple criteria ranking problem.

4.1. Data description

STI characteristics of Mexico and its regions have been studied by the Mexican scientific organization Foro Consultivo Científico y Tecnológico, AC [17,39]. They identified some indicators to measure the current state and progress of science and technology resources of the Mexican states. There was additional interest in establishing a standard based on reliable indicators that could serve as a tool for comparing the federal states as innovation systems, and support decision-making for the development of science and technology policies.

Starting in 2008, the FCCyT began a coordinated effort to gather and build a database of statistical information regarding a diverse set of innovation indicators. It resulted in a first edition of the study National Ranking for Science, Technology, and Innovation [17], which included 52 indicators across ten innovation dimensions.[1]

As stated before, FCCyT's original study organized the information related to science, technology, and innovation (STI) activities in a 10-dimensional structure that contained 52 indicators. The study aimed to create a global indicator of the STI resources available across the Mexican states to compare the states' innovative capacities (strengths and opportunities). The corresponding indicators for each dimension are presented in Table C.6 in Appendix C as elementary criteria and macro criteria, respectively. A brief description of the dimensions defined by the FCCyT [17] is presented below.

- Dimension 1. Research and Academic Infrastructure (ARI): This dimension seeks to measure the capacities for building human resources for STI and scientific productivity, from the perspective of academic infrastructure.
- Dimension 2. Human Resources (HR): This dimension measures the human capital potential of the States accounting for students' enrolment in academic settings, with a focus on the areas of science and technology.
- Dimension 3. Research Staff (RS): This dimension aims to measure the availability of qualified researchers' who contribute to human resource formation and scientific productivity.
- Dimension 4. STI Investment (STII): This dimension seeks to describe the amount of funding raised by the States for STI activities. Ideally, it tries to measure both public and private funding.
- Dimension 5. Science and Innovation Productivity (SIP): This attempts to measure the capacity for knowledge creation and innovation in each State, fundamentally through the counting of intellectual property.
- Dimension 6. Entrepreneurial Infrastructure (EI): The capacity for STI development is measured through indicators of business activities related to S&T.
- Dimension 7. Information and Communication Technologies (ICT): This dimension seeks to measure connectivity and IT development across the States.
- Dimension 8. Institutional Component (IC): This dimension focuses on the instruments in place that are used to generate public policy around STI activities in the States.
- Dimension 9. Gender in STI (GSTI): The objective of this dimension is to measure the participation of women in STI activities and its proportional comparison with the participation of men.
- Dimension 10. Social-Economic Environment (SEE): This final dimension seeks to describe the knowledge areas prioritized by each State through economic specialization indicators.

[1] A dimension concerns a characteristic that describes a measure of performance or the capacity of an element of the innovation system.

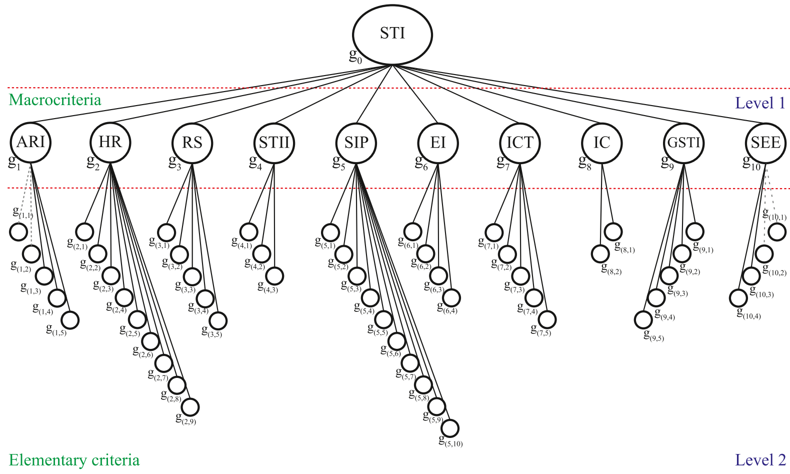

Fig. 5. Hierarchical structure of the science, technology and innovation (STI) problem.

4.2. *The expert of innovation capacity*

Furthermore, as part of the MCDA methodology, some information is required regarding the preferences attributed to the aforementioned indicators. Such a task falls in the hands of an expert, who in turn may or may not be the direct decision-maker concerning the innovation activities of the system. Since the innovation system as such is a conceptualization, and not an actual organization or enterprise devoted to the production of innovation, a "direct decision-maker" refers to those who are capable of influencing public policies that could impact different aspects of the interrelations within the components of the system, and consequently the performance of its activities.

However, in this particular study, the preferences for constructing the decision model are obtained from an expert specialized in innovation systems. The MCDA methodology throughout the MCHP supports the expert in the analysis of the innovation capacity of regions, thus providing a better way to report to a direct decision-maker.

4.3. *Applying the MCDA methodology with MCHP*

The application of the research methodology shown in Fig. 4 to address a real-world multiple criteria decision-making problem is performed below.

Step 1 Definition of the MCDA problem

The initial step is the definition of the MCDA problem. Hence, the study aims to analyse the appropriate innovation indicators in order to describe the characteristics that endow Mexico's regions with the capabilities required to generate economic growth through innovation activities. A multicriteria ranking of Mexican states will be generated regarding 52 decision criteria.

Step 2 Construction of the hierarchy

For the science, technology and innovation (STI) problem, ten dimensions are analysed. Each dimension refers to a subset of indicators that constitute the elementary criteria and the dimensions constitute the macro criteria. The hierarchy of criteria to analyse the STI problem is presented in Fig. 5.

Step 3 Definition of preferences

– Step 3.1 Applying the HDCM at all levels of hierarchy criteria

This step generates hierarchy weights for the STI problem. Two stages need to be performed in the hierarchical deck of cards method (HDCM). First, Stage 1 requires applying the SRF method to any set of subcriteria at each level of the hierarchy. To accomplish this task the preference information was elicited from the expert by requesting the ordering of macro criteria at Level 1 of the hierarchy and the elementary criteria at Level 2 of each subgroup. The expert defined from the least important macrocriterion (g4) to the most important (g1), as shown below.

(g4, ICT investment) ≺ (g8, Institutional component) ≺ (g9, Gender) ≺ (g6, Entrepreneurial Infrastructure) ≺ (g10, Social-Economic Environment) ≺ (g7, Information and Communication Technologies) ≺ (g5, Science and Innovation Productivity) ≺ (g2, Human Resources) ≺ (g3, Research Staff) ≺ (g1, Research and Academic Infrastructure)

For each macro-criterion, the expert ranked the elementary criteria from least to most important in relation to each sub-group of criteria only. Table 1 shows the ordering of each macro-criterion, the less important is ranked first, the most important is ranked 10^{th}. For example, for the macro criterion *ICT investment* (g4), the ordering of elementary criteria is (4,1) ≺ (4,3) ≺ (4,2); for the macro-criterion *Institutional component* (g8), (8,1) ≺ (8,2); and so on.

The preference information was the input for the computational tool Simos' Revised Procedure, and the weights were obtained at each level of the hierarchy. These generated weights are then translated into hierarchy weights in Stage 2 of the HDCM, integrating the subcriteria weights in a hierarchical relationship with the other subcriteria at all levels of the hierarchy in the multiple criteria hierarchy process.

The determination of the criteria weights using the SRF method requires the value of the parameter z, which is used to determine how many times the most important criterion is more important than the least important criterion. The z values used in each subgroup of criteria for the innovation capacity problem are listed in Table 2. For example, the first row of Table 2 shows macro criteria RAI (g1) used $z = 5$ for the subset of criteria {(1.5), (1,4), (1,3), (1,2), (1,1)} (listed from the least important to the most important).

In Table 3 an example of weights obtained by the application of the SRF method with different z values is shown. The weights shown in Table 3 are not used in the innovation capacity problem. The example is based on the five elementary criteria of macro-criterion RAI (g1). Column 2 lists the elementary criteria from least important at the top to most important at the bottom. In Column 3 the weights using the SRF method (regular) are shown. Column 4 shows the weights based on the hierarchy of criteria (HDCM). In $z = 5$ the difference between weight values for the hierarchy is 0.012. With $z = 2.5$ the difference is 0.007. The example shows the higher the z value, the greater the difference between weights.

– Step 3.2 Select and apply an aggregation method on macrocriteria

The Hierarchical ELECTRE III and distillation methods were applied to solve each subproblem (macro criterion) and the comprehensive level. The computational tools Hierarchical-ELECTREIII and

Table 1
Hierarchy weights for the STI problem generated with HDCM.

Pos.	Subcriterion	Weight	Pos.	Subcriterion	Weight
1	**STII (g4)**	**0.0182**	7	**SIP (g5)**	**0.1273**
	(4,1)	0.00303394		(5,8)	0.00231686
	(4,3)	0.00606606		(5,5)	0.00463372
	(4,2)	0.0091		(5,10)	0.00693785
2	**IC (g8)**	**0.0364**		(5,9)	0.00925471
	(8,1)	0.01213212		(5,7)	0.01157157
	(8,2)	0.02426788		(5,6)	0.01388843
3	**GSTI (g9)**	**0.0545**		(5,3)	0.01620529
	(9,3)	0.0036406		(5,4)	0.01852215
	(9,5)	0.00726485		(5,2)	0.02082628
	(9,2)	0.0109		(5,1)	0.02314314
	(9,1)	0.0145297	8	**HR (g2)**	**0.1455**
	(9,4)	0.01816485		(2,8)	0.0032301
4	**EI (g6)**	**0.0727**		(2,1)	0.0064602
	(6,4)	0.00727		(2,6)	0.00970485
	(6,3)	0.01454		(2,2)	0.01293495
	(6,2)	0.02181		(2,5)	0.01616505
	(6,1)	0.02908		(2,3)	0.01939515
5	**SEE g10**	**0.0909**		(2,4)	0.0226398
	(10,3)	0.00909		(2,7)	0.0258699
	(10,4)	0.01818		(2,9)	0.0291
	(10,1)	0.02727	9	**RS (g3)**	**0.1636**
	(10,2)	0.03636		(3,2)	0.01092848
6	**ICT (g7)**	**0.1091**		(3,4)	0.02180788
	(7,5)	0.00728788		(3,3)	0.03272
	(7,4)	0.01454303		(3,5)	0.04361576
	(7,3)	0.02182		(3,1)	0.05452788
	(7,1)	0.02908606	10	**RAI (g1)**	**0.1818**
	(7,2)	0.03636303		(1,5)	0.01214424
				(1,4)	0.02423394
				(1,3)	0.03636
				(1,2)	0.04846788
				(1,1)	0.06059394

Table 2
The z values used by the SRF method in each subgroup of criteria for the innovation capacity problem.

Subcriterion	z
RAI (g1)	5
HR (g2)	9
RS (g3)	5
STII (g4)	3
SIP (g5)	10
EI (g6)	4
ICT (g7)	5
IC (g8)	2
GSTI (g9)	5
SEE (g10)	4

distillation-ranking algorithm were used. Due to space limitations, details are reported in the online supplemental data appendix (H-IST.xlsx). Hence, the aggregated model (preference model) is also available at H-IST.

– Step 3.3 Generate ranking proposals in subproblems

The ranking-distillation algorithm allows the visualization of the result as complete preorders or partial preorders (see Chapter 2 in [33]). In the current application, as a visualization option, the median preorder from the distillation process was used to show a complete preorder of the 32 regions of Mexico.

Table 4 shows the ranking generated for each macro criterion and comprehensive level. The performances, inter-criteria and pseudo-criteria parameters, valued outranking relations, and corresponding rankings of the alternatives are available in the online supplemental data H-IST.

Table C.7 in Appendix C shows some differences between rankings of each macro criterion against the comprehensive ranking. For a ranking with 32 states, 496 pairs of comparisons are performed, following the $m * (m-1)/2$ equation. The number of pair differences ranges from 6 to 19. The macro-criterion most similar to the comprehensive problem is *STI invest* (g_4) and the macro-criterion most different to the comprehensive problem is *Institutional component* (g_8).

Step 4. Result analysis

To simplify the analysis of results obtained with the proposed method, we will focus our attention on the top five and bottom five states. The intention is to observe consistency throughout the different rankings obtained at the extremes of the rankings. With respect to the comprehensive ranking (g_0), the top five ranked states from top to bottom resulted in Mexico City (A_9), Nuevo León (A_{19}), Querétaro (A_{22}), Sonora (A_{26}) and Chihuahua (A_6).

In terms of the innovation dimensional structure presented in this study, these results are consistent with the reality of the conditions and capacities these states present regarding their infrastructure for innovation production. They rank from good to excellent in the positions they present for the different rankings, particularly for those that measure research conditions and capacities (i.e., research and academic infrastructure (g_1), human resources (g_2), STI investment (g_4), scientific and innovation productivity (g_5), information and communication technologies (g_7)) (see performances for regions in the online supplemental data). Furthermore, their position concerning Social-Economic Environment (g_{10}) places most of these states at the top of the ranking, suggesting a certain correlation between the conditions and capacities for innovation production, and the impact this has on the economy of the states.

From a regional perspective, the top five states in the general ranking are located in the central (A_9, A_{22}) and the northern border (A_{19}, A_{26}, A_6) regions of Mexico. Historically, these states have had some of the most favourable economic and development conditions

Table 3
Weights with different z value.

Position	Elementary criterion	z=5 regular	z=5 hierarchy	z=2.5 regular	z=2.5 hierarchy
1	g(1,5)	6.68	0.01214424	11.42	0.02076156
2	g(1,4)	13.33	0.02423394	15.75	0.0286335
3	g(1,3)	20	0.03636	19.98	0.03632364
4	g(1,2)	26.66	0.04846788	24.32	0.04421376
5	g(1,1)	33.33	0.06059394	28.53	0.05186754
Difference between weights		6.6	0.012	4.2	0.007

Table 4
Ranking of states on each macrocriterion and comprehensive level.

Pos.	Label	State	g1	g2	g3	g4	g5	g6	g7	g8	g9	g10	g0
1	A1	Aguascalientes	A25	A9	A22	A9	A9	A19	A9	A32	A13	A4	A9
2	A2	BCS	A26	A19	A17	A19	A19	A2	A19	A15	A29	A19	A19
3	A3	BC	A8	A26	A8	A22	A15	A1	A26	A10, A18	A30	A9	A22, A26
4	A4	Campeche	A9	A28	A3	A17	A22	A22	A2	A16	A20	A15	A6
5	A5	Chiapas	A2	A8, A31	A7	A15	A7	A7, A26	A1	A9	A14	A26	A2
6	A6	Chihuahua	A24	A22	A2	A21	A12	A15	A28	A5	A17	A22	A15
7	A7	Coahuila	A22	A6, A7	A1	A11	A31	A12	A25	A17	A6	A28	A8
8	A8	Colima	A7	A17	A6	A2	A1	A6	A23	A25	A15	A1	A1
9	A9	CDMX	A3	A2	A31	A6	A6	A24	A15	A11	A23	A23	A17
10	A10	Durango	A6	A3, A21	A15	A26	A17	A9	A3	A12	A18	A7	A3
11	A11	Edo. México	A16	A1	A21	A24	A21	A28	A7, A17	A1, A30	A9	A8, A31	A7
12	A12	Guanajuato	A29	A15	A29	A31	A26	A10	A8	A26	A27	A12	A25
13	A13	Guerrero	A15	A27	A24	A7	A24, A28	A3	A6	A6	A1	A27	A24
14	A14	Hidalgo	A31	A4	A10	A32	A2	A25	A24	A7	A26	A32	A31
15	A15	Jalisco	A1	A25	A32	A8, A12	A11	A31	A18	A14	A19	A21	A21
16	A16	Michoacán	A21	A10	A26	A3	A25	A29	A22	A31	A11, A24	A25	A28
17	A17	Morelos	A30	A32	A4	A16	A10	A11	A4	A21	A3	A2	A4
18	A18	Nayarit	A19	A24	A23	A10	A23	A14	A11	A20	A28	A6	A10
19	A19	NL	A14	A18	A16	A1	A3	A17	A31	A3, A4, A8, A28	A31	A20	A11
20	A20	Oaxaca	A11	A11	A18	A14	A32	A8	A10	A23	A21	A3	A12
21	A21	Puebla	A10	A14	A12	A28, A30	A8	A23	A32	A29	A5	A13	A23
22	A22	Querétaro	A32	A23	A9	A25	A16	A4	A14	A19	A10	A24	A32
23	A23	Quinta Roo	A12	A30	A19	A29	A29	A27	A12	A2, A13, A22	A16	A16, A30	A29
24	A24	SLP	A17	A12	A11	A23	A4	A21, A32	A30	A24	A8	A5	A16
25	A25	Sinaloa	A18	A29	A14	A18	A14	A30	A16, A29	A27	A22	A18	A18
26	A26	Sonora	A4	A16	A25	A5, A20	A30	A16	A21		A2	A14	A14, A30
27	A27	Tabasco	A28	A5	A20	A27	A5	A18	A27		A32	A11	A27
28	A28	Tamaulipas	A23	A13	A5	A4, A13	A27	A20	A13		A4	A10	A20
29	A29	Tlaxcala	A27	A20	A28		A18	A5	A5, A20		A7	A17	A5, A13
30	A30	Veracruz	A20		A30		A20	A13			A12	A29	
31	A31	Yucatán	A5		A27		A13				A25		
32	A32	Zacatecas	A13		A13								

Note: CDMX is the abbreviation of Mexico City.

Table B.5
Performance of the Revised Simos' Method.

Label	Criterion name	Position	Ranking cards	Position	White cards	Position	Weights
a	Group theory	1	$\{c, d\}$	1	$\{c, d\}$	1	$\{2.81, 2.81\}$
b	Linear algebra	2	$\{a\}$	2	$\{a\}$	2	$\{5.37\}$
c	Calculus	3	$\{e, h, j\}$	3	$\{e, h, j\}$	3	$\{7.93, 7.93, 7.93\}$
d	Functional analysis	4	$\{b, i\}$	4	$\{Whitecard\}$	4	$\{10.49, 10.49\}$
e	Analytical chemistry I	5	$\{f\}$	5	$\{b, i\}$	5	$\{13.04\}$
f	Analytical chemistry II	6	$\{g, k\}$	6	$\{f\}$	6	$\{15.60, 15.60\}$
g	Applied analytical chemistry			7	$\{g, k\}$		
h	Organic chemistry I						
i	Organic chemistry II						
j	Inorganic chemistry I						
k	Inorganic chemistry II						

relative to the rest of the country. The implication has been the capacity to concentrate a certain amount of wealth that has allowed them to develop the conditions necessary for STI production compared to other states that have struggled for many years with stagnant economies and precarious regional development.

Case in point, the last five states ranked in the comprehensive ranking (g_0), which is comprised (from top to bottom) of Veracruz (A_{30}), Tabasco (A_{27}), Oaxaca (A_{20}), Chiapas (A_5) and Guerrero (A_{13}). The result of the ranking of these states is a mirror image of the top five; most are present in the bottom five of every ranking obtained, especially in those that specifically concern STI resources. However, an impressive result is observed when dealing with g_9, which seeks to measure the conditions of gender concerning STI activities. Most of the bottom five states from g_0 are actually in the top five positions

Table C.6
Macrocriteria and elementary criteria of STI problem.

Index	Macrocriteria	Index	Elementary criterion name
1	**Research and Academic Infrastructure (RAI)**		
		(1,1)	Quality Graduate Programs Coverage for 2012 (%)
		(1,2)	Certified Undergraduate Programs Coverage for 2013 (%)
		(1,3)	Research Centers per/100,000 EAP in 2012
		(1,4)	HEI with Technology Programs per/10,000 residents between 20–29 y/o for 2011
		(1,5)	Technology Institutes of the Office of Public Education (SEP) per/100,000 EAP in 2012
2	**Human Resources (HR)**		
		(2,1)	CONACYT Scholarship Coverage 2012 (%)
		(2,2)	EAP with graduate title per/100,000 population 2012
		(2,3)	EAP with undergraduate title per/100,000 population 2012
		(2,4)	Graduate enrolment in S&T per/10,000 EAP 2010–2011
		(2,5)	Graduate enrolment in Social Sciences per/10,000 EAP 2010–2011
		(2,6)	Undergraduate enrolment in S&T per/10,000 EAP 2010–2011
		(2,7)	Undergraduate enrolment in Social Sciences per/10,000 EAP 2010–2011
		(2,8)	Enrolment in Technology Institutes per/10,000 EAP 2010–2011
		(2,9)	Undergraduate and Graduate enrolment per/10,000 population of 2011
3	**Research Staff (RS)**		
		(3,1)	Researchers in the National Researchers System (NRS) per/10,000 EAP in 2012
		(3,2)	Proportion of Graduate Staff to Graduate Enrolment 2010–2011 (%)
		(3,3)	Proportion of Undergraduate Staff to Undergraduate Enrolment 2010–2011 (%)
		(3,4)	Proportion of Technology Institutes Staff to Technological Education Enrolment 2012–2013 (%)
		(3,5)	Private Sector Researchers per/100,000 population in 2011
4	**STI Investment (STII)**		
		(4,1)	State Budget for STI as a percentage of State GDP 2012
		(4,2)	Private Expenditure in STI as a percentage of State GDP 2011
		(4,3)	CONACYT Funding for Human Resources as a Percentage of State Budget 2010–2012
5	**Science and Innovation Productivity (SIP)**		
		(5,1)	Awarded Patents per/100,000 population 2009–2012
		(5,2)	Patent Applications per/100,000 population 2010–2012
		(5,3)	Registration of Utility Models per/100,000 population 2009–2012
		(5,4)	Utility Model Applications per/100,000 population 2009–2012
		(5,5)	Registration of Industrial Designs per/100,000 population 2009–2012
		(5,6)	Industrial Design Applications per/100,000 population 2009–2012
		(5,7)	Average of Companies Innovating in Products and Processes per/10,000 Economic Units 2011
		(5,8)	Average of Companies Innovating in Organization and Commercialization per/10,000 Economic Units 2011
		(5,9)	Average Rate of Productivity of NRS Researchers 2002–2011
		(5,10)	Scientific Production Impact per State 2002–2011
6	**Entrepreneurial Infrastructure (EI)**		
		(6,1)	Innovative Companies per/10,000 Economic Units 2011
		(6,2)	RENIECYT Members per/10,000 Economic Units 2012
		(6,3)	Corporate Groups per/100,000 Occupied Population 2012
		(6,4)	Business Incubators per/100,000 Occupied Population 2012
7	**Information and Communication Technologies (ICT)**		
		(7,1)	Computer Users per/1000 EAP 2011
		(7,2)	Internet Users per/100,000 population over 6 y/o 2011
		(7,3)	Telephone Line Density 2010 (%)
		(7,4)	Cell Phone Contracts per/100 population 2012
		(7,5)	STI Communication Mediums per/100,000 population 2013
8	**Institutional Component (IC)**		
		(8,1)	Normative Framework for STI Planning 2012
		(8,2)	Proportion of Government Budget for STI as a Percentage of Total CONACYT Funding 2010–2012
9	**Gender in STI (GSTI)**		
		(9,1)	Percentage of CONACYT Scholarships by Gender 2012 (%)
		(9,2)	Percentage of STI Enrolment by Gender 2010–2011 (%)
		(9,3)	Percentage of Social Sciences Enrolment by Gender 2010–2011 (%)
		(9,4)	Gender Rate for NRS Researchers 2013 (%)
		(9,5)	Rate of Women Legislators for Science and Technology Commissions 2013 (%)
10	**Social-Economic Environment (SEE)**		
		(10,1)	Industrial Sector GDP per capita 2011
		(10,2)	Service Sector GDP per capita 2011
		(10,3)	Primary Sector Specialization Index 2011
		(10,4)	State Scientific Vocation Through Scientific Production 2011 (%)

Table C.7
Comparison of macrocriteria (g_r) rankings against comprehensive ranking (g_0).

	g1	g2	g3	g4	g5	g6	g7	g8	g9	g10
Differences between pairs	A1,A3	A1,A3	A1,A3	A1,A3	A1,A2	A1,A6	A1,A6	A1,A2	A1,A2	A1,A2
	A1,A7	A1,A7	A1,A6	A1,A7	A1,A6	A1,A8	A1,A8	A1,A5	A1,A8	A1,A4
	A2,A6	A2,A7	A1,A7	A2,A6	A1,A7	A2,A6	A2,A6	A1,A6	A2,A3	A1,A6
	A2,A8	A2,A8	A2,A3	A3,A7	A1,A8	A3,A7	A3,A6	A1,A8	A2,A5	A1,A8
	A3,A6	A3,A7	A2,A6	A4,A5	A2,A7	A3,A8	A3,A8	A2,A3	A2,A8	A2,A4
	A3,A7	(A6,A7)	A2,A7	A7,A8	A3,A7	A6,A7	A6,A7	A2,A4	A3,A8	A2,A6
	A6,A7	A6,A8	A2,A8		A3,A8	A7,A8	A6,A8	A2,A5	A4,A5	A2,A7
	A6,A8		A3,A6		A6,A7		A7,A8	A2,A7	A4,A7	A2,A8
			A6,A7		A7,A8			A2,A8	A5,A7	A3,A4
			A6,A8					(A3,A4)	A5,A8	A3,A7
								A3,A5		A4,A6
								A3,A7		A4,A7
								(A3,A8)		A4,A8
								A4,A5		A6,A7
								(A4,A8)		A6,A8
								A5,A6		A7,A8
								A5,A7		
								A5,A8		
								A7,A8		

Note: the pairs in parenthesis alternatives that are tied in one of the rankings.

of g_9 (A_{13}, A_{30}, A_{20}), which seems to indicate that the indicators that measure g_9 do not have a significant impact on the comprehensive ranking position of the states.

In terms of these states' regional location, the most of poor performers are located in the south of Mexico, a region of the country that has experienced the difficult economic and development conditions mentioned above. This is consistent once again, with the relationships that seem to exist between the social-economic development and the STI conditions and capabilities of these states.

4.4. Summary and discussion

With regards to the specific exercise this paper attempts to implement, it is pertinent to describe some key associated components. As previously mentioned, the context of this application revolves around the innovation activities carried out by the Mexican states, which are characterized as regional innovation systems. As proposed, a classification of science and technology indicators organized into innovation dimensions allows for the systemic evaluation of the performance of states as innovation systems.

The hope is that this information will have an impact on the efficiency of the public policy definition process by awarding the direct decision-makers with a more precise picture of the performance of the system, pinpointing its strengths and weaknesses, allowing for benchmarking exercises and revealing allocation needs within the system, among other things. Instead of what has been described, it should be noted that there is no direct impact of the results of the proposed methodology upon the innovation systems themselves. Instead, it should be viewed as a tool for gathering relevant information that forms part of a cumulative process that aims to give a more comprehensive picture of the state of innovation systems, giving the public policy makers the knowledge needed to make the most informed decisions regarding the innovation environment of the Mexican States.

5. Conclusion and future work

In this study, the problem of science, technology and innovation (STI) of the Mexican regions regarding different dimensions is addressed by the MCDA methodology by applying the Multiple Criteria Hierarchy Process (MCHP).

A main characteristic of the problem is number of criteria of the data analysed in the STI. It presents an important challenge related to the significant number of parameters defined by the expert. The application of the SRF method supports the definition of weights in the elicitation of expert preferences.

To apply the MCHP, the hierarchical version of Electre III and the distillation process were used for the construction of the preference model and ranking of alternatives, respectively. The interesting aspect of this approach is the analysis of the alternatives' performance, carried out with a different subset of criteria corresponding to different hierarchy levels.

We can highlight some limitations of the application. The Electre III method still requires the definition of indifference, preference and veto thresholds for each elementary criterion. Some indirect approaches, such as aggregation/disaggregation, seem to be necessary to reduce the effort required by the DM [40,41]. On the other hand, as more macro criteria are defined, more rankings need to be analysed. We have identified some lines of research to be developed based on these limitations.

CRediT authorship contribution statement

Pavel Anselmo Alvarez: Conceptualization, Methodology, Software, Resources, Validation, Formal analysis, Investigation, Writing – original draft, Writing – review & editing, Visualization, Project administration. **Cuitláhuac Valdez:** Conceptualization, Validation, Formal analysis, Investigation, Data curation, Writing – original draft, Writing – review & editing. **Bapi Dutta:** Conceptualization, Methodology, Validation, Writing – original draft, Writing – review & editing, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. The exploitation phase: the distillation procedure

In the exploitation phase, the distillation procedure analyses the fuzzy outranking relation. The distillation procedure measures the credibility of the asseveration of a_i outranks a_l with the value of $\sigma(a_i, a_l)$ and then presents a partial or complete preorder. It is generated from the descending and ascending distillation procedures, each showing a complete order.

The procedure finds $\sigma(a_i, a_l)$ corresponding to the highest value in the credibility matrix (A.1).

$$\lambda_0 = \max_{a_i, a_l \in A} \sigma(a_i, a_l) \tag{A.1}$$

Then the procedure estimates the distillation threshold function $s(\lambda_k)$ with the input parameters α and β.

$$s(\lambda_k) = \alpha \lambda_k + \beta, \tag{A.2}$$

where α and β are two thresholds that define the function $s(\lambda_k)$, which is a discrimination coefficient [33] for researching pairs where a_i is strictly preferred to a_l with a certain cut-off level. It is common to find $\alpha = -0.15$ and $\beta = 0.30$ as established values for the procedure.

We need to find the $\sigma(a_i, a_l)$ with the highest value at the next cut-off level $k+1$. At each subsequent level we will obtain $\sigma(a_i, a_l) < \lambda_k - s(\lambda_k)$.

$$\lambda_1 = \max_{\sigma(a_i, a_l) < \lambda_k - s(\lambda_k)} \sigma(a_i, a_l) \tag{A.3}$$

In the process, the comparison of credibility degrees for pairs $\sigma(a_i, a_l)$ and $\sigma(a_l, a_i)$ is carried out. The $aS^{\lambda_1}b$ condition states a relation of power and/or weakness between alternatives. $aS^{\lambda_1}b$ if and only if $\sigma(a_i, a_l) > \lambda_1$ and $\sigma(a_i, a_l) > \sigma(a_l, a_i) + (\alpha \times \sigma(a_i, a_l) + \beta)$.

In each distillation, we shall find a reduced value of λ_k, which corresponds to a better condition a_i is preferred than a_l for the remaining subset of pairs.

Process of descending distillation

The first time the procedure begins, Step 1 and Step 2 need to perform in sequence. Next, an iterative procedure is executed with the 1 The algorithm identifies the minimum subset of alternatives that meet the requirements for placement in the complete descending order. The procedure finishes when all the alternatives are placed in the complete order.

Step 1: Calculate (A.1) as the initial level to estimate the cut-off level (A.3) in order to identify the best remaining alternatives.

Step 2:

- **2.1** Find the highest degree of credibility with λ_k(A.1), estimate the next cut level λ_{k+1}(A.3) to find the maximum $\sigma(a_i, a_l)$ lower than $\lambda_k - s(\lambda_k)$. The subset of alternatives found with (A.3), are placed in the set D.
- **2.2** Calculation of power, weakness and qualification of alternatives from D. Every time a_i outranks a_l, the strength of a_i increases by 1 and the weakness of a_l increases by -1. For each alternative, the strengths and weaknesses are added together to give a final qualification score.
- **2.3** Select the alternatives with higher qualification, conforming the set D'.

The Ascending distillation performs a similar procedure in the opposite direction; the alternatives with the lowest qualification scores are assigned to the last positions in the ranking. The ranking is constructed from the bottom to the top.

The intersection between descending and ascending preorders

For the intersection between complete preorders, we need to find strict preferences in pairs of alternatives between preorders.

Algorithm 1: Placing alternatives for the complete descending order

```
if |D| > 1 and λ_k ≠ 0 then
    Repeat step 2
else
    A = A\D′
    Add D′ to complete_descending_preorder
    D = ∅, D′ = ∅
    Return to the Step 1
end
```

- a_i *is strictly preferred to* a_l if a_i is better positioned than a_l in at least one of the rankings, and if a_i is at least as good as a_l in the other rank.
- a_i *is indifferent to* a_l if a_i and a_l are placed in the same position (belong to same group) in the two rankings.
- a_i *is incomparable to* a_l if a_i is better positioned than a_l in one ranking and a_l is better positioned than a_i in the other ranking.

Appendix B. The revised Simos' procedure

B.1. Summary of the Simos–Roy–Figueira (SRF) method

Step 1. *Preparing cards*: A set of cards (n cards) representing criteria are given to the user. They contain the criterion name or other necessary information. The user is also given same size of white cards.

Step 2. *Ranking cards*: The user ranks the cards (criteria) from the least important to the most important. In this sense, the first criterion is the least important and the last criterion is the most important. Criteria with same level of importance are defined when corresponding cards are grouped in the same set of cards.

Step 3. *Introducing white cards*: The user needs to think about the importance of the difference between two successive criteria (card a > card b, card a > set of cards, set of cards > card a, set of cards > set of cards). The greater the difference, the greater the importance of the next card (or set of cards). The way to express this difference in importance is to insert blank cards between two successive sets of equivalent cards (i.e., criteria with the same importance).

Step 4: *Determining weights*: Apply the SRF Method. At least one input is required to apply the SRF, the z value is an input relative to how many times the most important set of criteria is more important than the least important in the ranking.

Appendix C. Science, technology and innovation capacities

See Tables C.6 and C.7 .

Appendix D. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.seps.2022.101418.

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