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Assessing Public Safety of Cities using A Hierarchical Interval Outranking Approach

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Abstract: This work proposes a multicriteria decision-making model to evaluate cities in terms of public safety. The proposed approach can handle data uncertainty and heterogeneity while recognizing public safety as a multifaceted issue that is influenced by various (often many) factors. It compares decision alternatives through a hierarchy of criteria and sub-criteria, facilitating a comprehensive evaluation of safety and accommodating the inherent uncertainty in crime measurement. The model integrates crime data, public security resources, and perceptions of insecurity. This approach can categorize cities into classes ranked by their public safety levels, addressing high, medium, and low-impact crimes according to policymakers' preferences. The approach is illustrated throughout the paper in a case study with Mexico's capital cities. The results reveal significant disparities in safety across cities, offering valuable insights into which capitals face the greatest challenges in achieving sustainable security.

Keywords: *Public safety; multicriteria decision analysis; outranking approach; interval-based analysis; urban security*

Introduction

Public safety is a critical concern in Mexico, a country with a federal structure comprising 31 states, each with a capital that serves not only as a governmental center but also as a hub of intense economic, administrative, social, and cultural activity. These cities, diverse in their history, sociodemographic profiles, and institutional capacities, share the common problem of increasing insecurity and violence, which undermines sustainable development. Over the past decade, this phenomenon has escalated, particularly affecting urban areas and regions bordering the United States of America (Calonge-Reillo, 2021; Garza, 1999; Nuñez et al., 2017).

Crimes of common jurisdiction refer to those that directly impact individuals, meaning the consequences fall on the victims of the criminal actions. The year 2020 was particularly critical, with a high incidence of such crimes (1,841,188), including a notable increase in intentional homicides (28,830), resulting in a rate of 22.56 deaths per 100,000 inhabitants (SESNSP, 2020). This pattern of criminality is not uniformly distributed across the country but is concentrated in certain states, prompting the government to identify and prioritize certain areas (SESNSP, 2020). Evaluating crimes of common jurisdiction in Mexico's capital cities presents a complex challenge due to the need to address multiple dimensions influencing public safety and sustainable development. These dimensions include enhancing security, preventing crime, optimizing resources, and reducing response times of security forces. Effective public safety management is integral to ensuring the environmental, cultural, economic, and social sustainability of these cities. For instance, high crime rates can deter economic investment, disrupt social cohesion, and negatively impact the cultural vitality of urban centers, all of which are essential components of sustainable development.

State and municipal police forces are responsible for preventing and addressing these types of crimes to protect the citizenry. The main stakeholders in this process include public decision-makers, technical evaluators, direct and indirect beneficiaries of the public policy in question, and community representatives. In this study, the decision-making scenario is set in the state capitals, where state and federal public security authorities (the State and Federal Secretariats of Public Security) act as the primary

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policymakers. These authorities are responsible for designing and implementing the most effective tactical security strategies to ensure that the state capitals achieve the highest possible level of public safety and sustainable development (Plottu & Plottu, 2011).

The growing concern over public safety in Mexico's capital cities is driven by various factors, including socio-economic disparities, ineffective law enforcement, and the pervasive influence of organized crime. These issues not only affect the immediate safety of residents but also have long-term implications for the sustainability of these cities. The population in these capital cities accounts for 17.9 percent of the national total, underscoring the importance of strategically planning public safety and sustainable development given the considerable use of human, economic, and technical resources. Moreover, public safety and crime victimization directly impact the quality of life and long-term sustainability of communities, affecting environmental integrity, cultural preservation, economic stability, and social cohesion (Hanson et al., 2010; Huimin et al., 2020; Piroozfar et al., 2019; Vilalta & Muggah, 2016). Therefore, it is imperative to develop formal procedures to determine the relative level of public safety in these capitals and establish appropriate planning strategies for the three levels of government (Massa & Fondevila, 2021).

This study seeks to address several central questions: How can all relevant dimensions be integrated into a model that evaluates the relative level of public safety in a capital city? Which model could policymakers use to establish the best classification of cities that reflects their relative level of public safety and represents governmental objectives? Furthermore, which cities are the safest or most insecure in the country, and what dimensions explain their position in the national ranking?

Traditional methods of evaluating public safety often fall short in capturing the full spectrum of factors that influence safety perceptions and realities in urban environments. These methods typically rely on crime statistics and other quantitative measures, which, while useful, do not fully account for the nuances and complexities inherent in public safety issues and their impact on sustainable development (Majmundar & Weisburd, 2018; Walker & Archbold, 2018). On the other hand, the assessment of crime across multiple cities using a multicriteria approach has been explored by relatively few experts (Basilio et al., 2020; Figueiredo & Mota, 2016; Gurgel & Mota, 2013; Leyva-Lopez & Fernandez-Gonzalez, 2003). Most research has focused on identifying the factors that influence public insecurity and their impact levels through multidimensional statistical methods (Clancy et al., 2022; Lisowska-Kierepka, 2022; Luo et al., 2022). Some studies evaluate the performance of various factors or schemes via a cost function that integrates multiple measures affecting public safety, considering perspectives from victims, the government, and society, such as lost productivity, pain and suffering, medical expenses, and the criminal justice system (Ohene Opoku et al., 2021; Wickramasekera et al., 2015). Other researchers examine public safety in a city by independently evaluating various factors, conducting specific factor-by-factor analyses (Flores Gamboa & Leyva López, 2018). Evaluating and comparing the incidence of common crimes across a group of cities presents significant challenges due to the complexity of integrating multiple criteria, which are often incompatible. Previous methods have failed to encompass all necessary aspects for a comprehensive assessment, leading to a loss of information, especially when measuring the consequences of the values or utilities involved. Assessing the incidence of common crimes in a set of cities while evaluating multiple criteria simultaneously is therefore complex. Hence, it is crucial to develop a procedure that allows for a comprehensive evaluation among capital cities, including all relevant criteria regardless of their incompatibility. Additionally, the evaluation method must consider the rationality of policymakers, as this process involves representing the objectives and changes of government across different administrative levels. Thus, the evaluation procedure should capture the preferences of a specific policymaker in a given situation.

To address these limitations, this study proposes a novel assessment model based on a hierarchical interval outranking model derived from Multicriteria Decision Analysis (MCDA) (Fernández et al., 2022). This approach allows for a more comprehensive and nuanced evaluation by incorporating multiple criteria and addressing the inherent uncertainty and heterogeneity of public safety data.

MCDA is a well-established decision-making framework that facilitates the evaluation of alternatives based on multiple, often conflicting criteria. It has been widely applied in various fields, including environmental management, transportation planning, and healthcare. In the context of public safety and sustainability, MCDA provides a structured approach to integrating diverse factors such as crime rates, law enforcement effectiveness, and public perceptions of safety. By using a hierarchical interval outranking model, this study better captures the uncertainty and variability in public safety metrics (Keeney, 1992; Linkov et al., 2005). The hierarchical outranking approach used in this study is particularly well-suited for evaluating public safety in urban environments. This method allows for the comparison of decision alternatives through a structured hierarchy of criteria and sub-criteria, facilitating a comprehensive evaluation of safety in each capital city. The use of interval-based data further enhances the model's ability to accommodate the inherent uncertainty in crime measurement and reporting. This is crucial in contexts like public safety, where data quality and reliability can vary significantly (Roy, 1996). This model uses crime data, public security resources, and perceptions of insecurity extracted from reliable national databases. By incorporating these diverse data sources, the model offers a holistic view of public safety, highlighting significant differences among cities and providing insights into which capitals face the greatest challenges (Delgado & Wences, 2020).

The practical implications of this study are manifold. Firstly, the results of the model can inform policymakers about the relative safety levels of different cities, helping them prioritize resource allocation and policy interventions. Secondly, the model's ability to handle interval-based data makes it a valuable tool for managing the uncertainty inherent in public safety evaluations. This is particularly important in the context of Mexico, where data on crime and public safety are often inconsistent and incomplete. Lastly, the hierarchical structure of the model allows for a more nuanced analysis, capturing the interactions between different criteria and providing a deeper understanding of the factors that influence public safety and sustainability (McCarthy et al., 2023; Sherman, 2002).

The rest of the paper is structured as follows. In Section 2, we provide a detailed account of the materials and methods employed in our study, explaining how these components are integrated to form a comprehensive methodology for addressing the problem. Section 3 presents the case study, outlining the application of our proposed model and discussing the results obtained from this application. Finally, Section 4 offers concluding remarks, summarizing the key findings and implications of our work and providing future research lines.

Materials and methods

This section outlines the materials and methods utilized in this work. The methodology integrates various components from MCDA to address the complexities and uncertainties inherent in public safety data. We start by explaining the data required by such components, we build such data as a hierarchical structure and, later, we provide the details of each component.

Data collection

The data used in this study were collected from reliable national databases, including:

I. Crime statistics such as data on crime rates, types of crimes, and their frequencies were obtained from the National System of Public Security (SESNSP, 2020).

II. Law enforcement resources that provide information regarding the availability and distribution of law enforcement resources, such as police personnel and equipment, sourced from government reports (Secretariado Ejecutivo del Sistema Nacional de Seguridad Pública, 2020).

III. Public perceptions of safety obtained by official surveys and studies conducted by national research institutions which provide insights into the public's perception of safety and their experiences with crime (CONAPO, 2020; ENSU-INEGI, 2020).

Socio-economic indicators including unemployment rates, income levels, and educational attainment were gathered from the National Institute of Statistics and Geography (ENAOE-INEGI, 2020; INEGI, 2023).

Hierarchical structure of criteria

In this phase, policymakers establish their objectives using the so-called Value-Focused Thinking (VFT) methodology (Keeney, 1992) which considers three levels: strategic, fundamental, and means-end objectives. Here, the strategic objective is classifying Mexico's capital cities based on their relative levels of violence. This strategic goal is further divided into two fundamental objectives: improving public safety in state capitals and enhancing the capacity for crime prevention in these cities. Both objectives are complemented by means-ends goals that require the specification of attributes to measure the degree of achievement attained.

The two means-end objectives are described as follows.

Improve Public Safety in State Capitals: This objective involves enhancing the prevention of common jurisdiction crimes to significantly decrease their frequency. Alternatively, it seeks to expand public safety by minimizing medium and low-impact social crimes and reducing various types of theft and property crimes, which create an atmosphere of insecurity and increase the vulnerability of the population.

Enhance the Capacity for Crime Prevention in Capital Cities: This entails reviewing and choosing efficient methods to improve performance metrics in public safety initiatives, including tackling social inequality and enhancing education.

This three-level structure, illustrated in Figure 1, facilitates a detailed assessment of the cities based on twelve elemental criteria collected from public databases (CONAPO, 2020; ENAOE-INEGI, 2020; ENSU-INEGI, 2020; Leyva et al., 2023; SESNSP, 2020). These criteria were carefully selected to align with the proposed objectives of the case study in such a way that there are no redundancies.

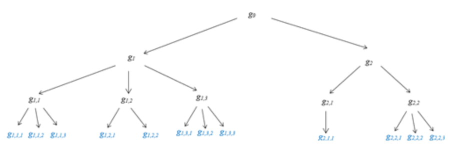

Figure 1. Hierarchical structure of the elementary criteria used to evaluate capital cities.

Table 1 details the twelve elemental criteria that form the basis of the multicriteria decision support model. Within this structure, categories such as High-Impact Crimes ($g_{1,1}$), Medium-Impact Crimes ($g_{1,2}$), Low-Impact Crimes ($g_{1,3}$), Allocation of Resources for Public Security ($g_{2,1}$), and Social Prevention of Violence and Crime ($g_{2,2}$) are distinguished as macro-criteria or non-elemental criteria. The first three are part of the macro-criterion related to Strengthening Public Safety Levels in Capital Cities (g_1), while the latter two constitute the macro-criterion associated with Increasing Crime Prevention in Capital Cities (g_2).

To compose these macro-criteria, the following elemental criteria are descendants:

- From High-Impact Crimes: Homicides ($g_{1,1,1}$), Kidnappings ($g_{1,1,2}$), and Rapes ($g_{1,1,3}$).
- From Medium-Impact Crimes: Property Crimes ($g_{1,2,1}$) and Injuries ($g_{1,2,2}$).
- From Low-Impact Crimes: Common Theft ($g_{1,3,1}$), Bank Robberies ($g_{1,3,2}$), and Other Crimes ($g_{1,3,3}$).
- Derived from the Allocation of Resources for Public Security: Strengthening Public Security Performance ($g_{2,1,1}$).
- From Social Prevention of Violence and Crime: Perception of Insecurity ($g_{2,2,1}$), Unemployment Rate ($g_{2,2,2}$), and Marginalization ($g_{2,2,3}$).

All criteria (except $g_{2,1,1}$) are to be minimized, indicating that the lower the impact on these criteria, the higher the preference from the decision-maker's perspective. Each of these elemental criteria not only represents means-end objectives but also has a specific functional representation that directly influences the public safety of the capital cities. As previously described, it is crucial to minimize high, medium, and low-impact crimes, as this has a direct effect on public safety.

Table 1. Elementary criteria that make up the multi-criteria decision support model

Code	Criterion	Maximum Value (%)
$g_{1,1,1}$	Homicides	Homicide rate per hundred thousand inhabitants.
$g_{1,1,2}$	Kidnappings	Kidnapping rate per hundred thousand inhabitants.
$g_{1,1,3}$	Rapes	Rate of rape of women per hundred thousand inhabitants.
$g_{1,2,1}$	Property Crimes	Property crime rate per hundred thousand inhabitants.
$g_{1,2,2}$	Injuries	Injury rate per hundred thousand inhabitants.
$g_{1,3,1}$	Common Theft	Common theft rate per hundred thousand inhabitants.
$g_{1,3,2}$	Bank robberies	Rate of bank robberies per hundred thousand inhabitants.
$g_{1,3,3}$	Other Crimes	Rate of other crimes per hundred thousand inhabitants.
$g_{2,1,1}$	Strengthening Performance for Public Safety	Millions of Mexican pesos invested in equipment, infrastructure and training of police and public security personnel.
$g_{2,2,1}$	Perception of Insecurity	The percentage of the population over 18 years of age who in December 2020 felt unsafe in their city.
$g_{2,2,2}$	Unemployment rate	Percentage of unemployment of the population over 15 years of age in urban cities with 100,000 inhabitants or more.
$g_{2,2,3}$	Marginalization	Index that differentiates the municipalities of the country according to the global impact of the deficiencies suffered by the population due to lack of access to education, residence in inadequate housing, the perception of insufficient monetary income and those related to residing in localities with little access to basic services.

Interval theory

Consider a scenario where a group of citizens is tasked with evaluating the public safety of Mexico's 31 capital cities based on the criterion "Perception of Insecurity", $g_{2,2,1}$. Despite a consensus-reaching process, variations in the assessments remain due to differing opinions, experiences, and sources of information. The policymaker, acting as the highest decision authority, decides to represent these diverse assessments using interval numbers.

Interval numbers are magnitudes whose precise values are not known but are confined within a defined range of real numbers (Moore, 1963). For example, if the perception of insecurity in a particular city is assessed differently by the citizens, with estimates ranging from 40% to 60%, an interval number can effectively capture this range as [40%, 60%]. Interval numbers allows to encompass the uncertainty and variability involved in the perception of insecurity in each capital city. Below, we provide some arithmetic used in the interval theory.

Consider two interval numbers $\boldsymbol{D} = [\underline{D}, \overline{D}]$ and $\boldsymbol{E} = [\underline{E}, \overline{E}]$. Two fundamental arithmetic operations are as follows:

$$\boldsymbol{D} + \boldsymbol{E} = \left[\underline{D} + \underline{E}, \overline{D} + \overline{E}\right],$$

$$\boldsymbol{D} \times \boldsymbol{E} = \left[\min\left\{\underline{D}\underline{E}, \underline{D}\overline{E}, \overline{D}\underline{E}, \overline{D}\overline{E}\right\}, \max\left\{\underline{D}\underline{E}, \underline{D}\overline{E}, \overline{D}\underline{E}, \overline{D}\overline{E}\right\}\right],$$

An order relation on interval numbers can be defined by using the possibility function introduced by (Shi et al., 2005).

$$Poss(\boldsymbol{E} \geq \boldsymbol{D}) = \begin{cases} 1 \ \ if \ p_{ED} > 1 , \\ p_{ED} \ \ if \ \ 0 \leq p_{ED} \leq 1, \\ 0 \ \ if \ p_{ED} \leq 0, \end{cases}$$

where

$$p_{ED} = \frac{\overline{E} - \underline{D}}{\left(\overline{E} - \underline{E}\right) + \left(\overline{D} - \underline{D}\right)}$$

Assessing capital cities

Consider a scenario where a group of citizens is tasked with evaluating the public safety of Mexico's 31 capital cities based on the criterion "Perception of Insecurity", $g_{2,2,1}$. Despite a consensus-reaching process, variations in the assessments remain due to differing opinions, experiences, and sources of information. The policymaker, acting as the highest decision authority, decides to represent these diverse assessments using interval numbers.

Table 2. Capital cities considered in this work

Code	Capital City	Code	Capital City
A_1	Acapulco	A_{17}	Morelia
A_2	Aguascalientes	A_{18}	Oaxaca
A_3	Campeche	A_{19}	Othón P. Blanco
A_4	Centro (Villahermosa)	A_{20}	Pachuca
A_5	Chihuahua	A_{21}	Puebla
A_6	Colima	A_{22}	Querétaro
A_7	Cuernavaca	A_{23}	Saltillo
A_8	Culiacán	A_{24}	San Luis Potosí
A_9	Durango	A_{25}	Tepic
A_{10}	Guadalajara	A_{26}	Tlaxcala
A_{11}	León	A_{27}	Toluca
A_{12}	Hermosillo	A_{28}	Tuxtla Gutiérrez
A_{13}	La Paz	A_{29}	Victoria
A_{14}	Mérida	A_{30}	Xalapa
A_{15}	Mexicali	A_{31}	Zacatecas
A_{16}	Monterrey		

The assessment of the capital cities on the elementary criteria is shown in Table 3.

Table 3. Assessment of capital cities on the elementary criteria

City	$g_{1,1,1}$	$g_{1,1,2}$	$g_{1,1,3}$	$g_{1,2,1}$	$g_{1,2,2}$	$g_{1,3,1}$	$g_{1,3,2}$	$g_{1,3,3}$	$g_{2,1,1}$	$g_{2,2,1}$	$g_{2,2,2}$	$g_{2,2,3}$
A_1	52.44	0.77	16.16	146.09	77.02	96.82	0.90	299.76	5028204.08	[74.96,82.85]	4.86	-0.58
A_2	11.96	0.74	24.76	515.37	306.13	481.79	0.00	630.00	3345546.74	[42.94,47.46]	5.87	-1.32
A_3	8.50	0.00	27.92	19.38	16.32	55.33	0.00	53.11	3839740.66	[39.81,44]	3.95	-1.14
A_4	34.57	1.02	14.36	239.50	252.14	570.31	0.00	973.40	1364083.02	[88.16,97.44]	7.89	-1.22
A_5	41.06	0.00	35.38	398.77	132.54	119.35	0.21	172.15	1254131.13	[57.67,63.74]	5.42	-1.39
A_6	58.67	1.27	33.11	871.22	340.95	627.17	0.00	1460.34	9170552.51	[73.91,81.69]	4.47	-1.16
A_7	49.73	1.59	31.76	531.98	258.38	806.89	1.59	1076.75	4395830.55	[88.07,97.34]	3.25	-1.25
A_8	58.19	0.30	6.88	108.85	94.75	78.60	1.20	200.45	3019848.63	[61.28,67.73]	2.68	-1.20
A_9	12.18	0.00	20.91	396.44	196.69	380.52	0.15	488.19	3243706.93	[41.9,46.31]	5.41	-1.25
A_{10}	33.20	0.22	6.64	404.67	135.86	818.70	0.87	887.27	4009484.52	[88.54,97.86]	4.72	-1.34
A_{11}	43.29	0.06	4.18	257.67	158.61	48.87	0.06	271.66	1696128.15	[80.75,89.25]	6.37	-1.05
A_{12}	28.94	0.11	12.71	130.03	57.44	87.02	0.00	226.97	3852961.09	[65.84,72.77]	3.60	-1.26

A_{13}	9.95	0.34	28.06	395.99	262.55	69.30	0.00	573.20	5644920.91	[29.26,32.34]	4.26	-1.10
A_{14}	6.63	0.00	0.80	237.90	18.49	481.59	0.20	846.89	5228185.03	[22.42,24.78]	3.31	-1.28
A_{15}	25.34	0.19	21.19	350.60	276.76	209.33	0.10	633.69	2922715.04	[64.6,71.4]	2.40	-1.24
A_{16}	23.97	0.17	21.88	305.39	90.63	170.74	0.44	332.84	2676738.02	[66.41,73.4]	4.43	-1.33
A_{17}	60.89	0.94	17.37	319.44	250.01	204.00	0.00	355.22	2827991.99	[70.02,77.39]	3.91	-1.18
A_{18}	45.44	0.74	32.63	394.48	334.04	246.93	0.37	628.20	7122691.07	[73.34,81.06]	3.36	-0.96
A_{19}	71.76	0.43	36.80	506.42	221.70	527.10	0.00	1179.94	3919517.74	[58.62,64.79]	4.80	-0.97
A_{20}	21.68	0.95	32.68	378.49	370.67	1134.73	6.04	1066.40	6048320.76	[54.91,60.69]	3.82	-1.26
A_{21}	11.23	0.41	14.66	96.73	56.18	367.16	0.00	539.90	1319831.55	[70.49,77.91]	6.69	-1.13
A_{22}	16.77	0.57	31.39	323.26	284.72	26.20	0.10	250.57	3275916.98	[42.09,46.52]	5.69	-1.25
A_{23}	8.30	0.45	8.18	154.69	122.60	354.25	0.00	650.51	3265603.54	[32.21,35.6]	5.75	-1.38
A_{24}	30.90	1.32	31.28	465.50	192.79	21.58	0.00	189.75	2941475.82	[90.25,99.75]	5.03	-1.28
A_{25}	11.80	0.47	13.32	40.03	17.31	28.53	0.00	27.58	1476611.97	[44.75,49.46]	4.26	-1.21
A_{26}	11.01	3.00	4.00	55.06	36.04	5852.79	0.00	8660.70	8105506.62	[47.5,52.5]	5.52	-1.28
A_{27}	18.56	0.77	11.98	342.80	499.99	30.99	0.00	72.51	2482416.30	[77.43,85.58]	5.28	-1.06
A_{28}	11.08	0.00	12.75	79.94	39.86	92.09	0.00	168.19	2512935.63	[63.84,70.56]	5.92	-1.07
A_{29}	44.61	0.86	14.73	238.20	102.10	283.54	0.29	542.01	4603167.31	[38,42]	6.40	-1.26
A_{30}	15.38	1.23	9.21	328.11	145.47	26.04	0.00	349.98	3527173.93	[60.42,66.78]	4.81	-1.13
A_{31}	66.50	4.01	17.38	599.24	206.26	2405.75	0.00	6005.40	9188232.18	[87.31,96.5]	4.88	-1.34

Hierarchical interval outranking approach

The so-called outranking approach is widely mentioned in the literature regarding MCDA. This approach is a multi-criteria decision methodology that is used to rank, sort (ordinal classification) or select among several possible options. From the MCDA literature, the family of ELECTRE ("ELimination Et Choix Traduisant la REalité") are the most prominent methods that use the outranking approach.

While traditional ELECTRE methods are effective in many scenarios, they have limitations when dealing with uncertain or imprecise data, which are common in real-world decision-making. Furthermore, many decision-making problems are very complex and, assessing an alternative in a given criterion requires the alternative to be also assessed on sub-criteria. This is where interval-based hierarchical outranking comes into play. Recently, (Fernández et al., 2022) proposed an extension of the ELECTRE methods, a method called interval-based hierarchical outranking approach. The new approach allows to handle uncertainty and imprecision in the data through the interval theory while also can deal with complex hierarchical structures of criteria.

For homogeneity purposes, we will use here part of the notation adopted by (Fernández et al., 2022).

- Let A be the set of alternatives (potential actions).
- Let Ig be the set of indexes of all criteria in the hierarchy.
- Let $\chi = \{g_0, g_1, \ldots g_{card(Ig)}\}$ be the set of all criteria in the hierarchy. Without loss of generality, we assume that preference increases in the sense of criterion values.
- Let EL be the set of indices of all elementary criteria.
- Let N_h be the number of immediate sub-criteria of a non-elementary criterion g_h.
- Let $G_h = \{g_{h1}, \ldots g_{hNh}\}$ be the set of immediate sub-criteria of a non-elementary criterion g_h. If $g_j \in G_h$, then g_j is said to be an immediately descending criterion of g_h, and this is an immediately ascending criterion of g_j.
- Let I_{Gh} be the set of indices of all criteria in G_h.
- Let $EL(h)$ be the set of indices of all elementary criteria that influence a non-elementary criterion g_h;

- Let $D(h)$ be the set of indices of all criteria influencing a non-elementary criterion g_h from a lower hierarchical level; When $j \in D(h)$, then g_j is said to be a descendant of g_h.

The following concepts are added to the notation:

- Let EL_p, subset of EL, be the set of indices of all criteria that are pseudo-criteria, i.e., the subset of criteria where the performance of alternatives is not measured using interval numbers.
- Let EL_I, subset of EL, be the set of indices of all criteria that are interval numbers.

(Fernández et al., 2022) recommend using a partial outranking relationship, denoted as $Sj \subseteq A \times A$, associated with each criterion $g_j \in EL$. This serves to signal that "a is at least as good as b from the perspective of g_j" ($a, b \in A \times A$), along with a degree of credibility that is satisfied aS_jb, $\delta_j(a, b)$. The calculation of $\delta_j(a, b)$ depends on whether g_j is a pseudo-criterion or an interval number. Thus, when g_j is an interval number, that is, $g_j \in EL_I$:

$\delta_j(a, b) = P(\boldsymbol{g}_\mathbf{j}(a) \geq \boldsymbol{g}_\mathbf{j}(b))$.

And when $g_j \in EL_P$:

$$\delta_j(a, b) = \begin{cases} 1 & \text{if} \quad g_j(b) - g_j(a) \geq p_j, \\ \frac{g_j(a) - g_j(b) + p_j}{p_j - q_j} & \text{if} \quad g_j(b) - p_j \leq g_j(a) < g_j(b) - q_j, \\ 0 & \text{if} \quad g_j(a) - g_j(b) \geq -q_j. \end{cases}$$

where p_j and q_j represent the preference and indifference thresholds for the criterion g_j. The first establishes a range where the policymaker has a strict preference for one of the alternatives; the second establishes a range where the policymaker is indifferent given that the performance of the alternatives is similar enough.

Now, the degree of credibility of aS_hb when $h \notin EL$, denoted by $\sigma_h(a,b)$, can be computed recursively by adding all $\sigma_j(a,b)$ values to $g_j \in G_h$, note that, when $g_j \in EL$, then:

$$\sigma_j(a, b) = \delta_j(a, b) \qquad (1)$$

Such aggregation requires a criterion weight (considered as a relative importance coefficient) that must be defined for each $g_j \in G_h$; let us denote this weight by w_{jh}. Other parameters associated with $g_j \in G_h$ can also be defined such as a veto threshold, v_{jh} (rejecting any credibility of aS_hb if $g_j(b)$ exceeds $g_j(a)$ by an amount greater than v_{jh}). These parameters allow the calculation of a Concordance-γ index related to S_h, $c_h(a,b,\gamma)$. This value represents the support of the coalition of criteria in accordance with aS_hb, where γ is the highest credibility value of these criteria that support the claim. The degree of credibility of the statement "the considered γ-concordance coalition is sufficiently strong" is then calculated as $P(c_h(a,b,\gamma) \geq \lambda_h)$, where λ_h is a threshold set by the DM to establish what It is a strong majority. The reader is referred to (Fernández et al., 2022) to see the details in the calculation of $c_h(a,b,\gamma)$, as well as some restrictions that the parameters mentioned above must meet.

Ordinal ranking using interval-based hierarchical outranking approach

Using the notation introduced above, the interval-based hierarchical outranking approach can be exploited to perform the ordinal classification of the capital cities using the following procedure (Fernández et al., 2022):

The HI-INTERCLASS-nC method is a novel method that exploits the interval-based hierarchical outranking approach to assign alternatives to preferentially ordered classes. This methodology allows assignments to be made at the level of any non-elementary criterion g_h. C^h is defined as a finite set of classes $C^h = \{C_1, \ldots, C_{ki}, \ldots, C_M\}^h$, $M \geq 2$, ordered with increasing preference with respect to g_h. The subset $R_k = \{r_{k,j}, j = 1, \ldots, \text{card}(R_k)\}$ represents the reference alternatives that characterize C_k, with $k = 1, \ldots, M$. The total set of reference alternatives is $\{r_0, R_1, \ldots, R_M, r_{M+1}\}$, where r_0 and r_{M+1} are the anti-ideal and ideal alternatives, respectively.

The credibility indices between an alternative a and the class Ck are defined as:

$$\sigma_h(\{a\}, R_k) = \max_{j=1,\ldots,card(R_k)} \{\sigma_h(a, r_{k,j})\}$$

$$\sigma_h(R_k,\{a\}) = \max_{j=1,\ldots,card(R_k)} \{\sigma_h(r_{k,j}, a)\}$$

Where $\sigma_h(a, r_{k,j})$ is calculated through Eq. (1).

For given $\beta > 0.5$, hierarchical categorical outranking relationships are defined as follows:

a) $aS_h(\beta)R_k \Leftrightarrow \sigma_h(\{a\}, R_k) \geq \beta$;

b) $R_kS_h(\beta)a \Leftrightarrow \sigma_h(R_k,\{a\}) \geq \beta$.

The selection function is defined as: $i_h(\{a\}, R_k) = \min\{\sigma_h(\{a\}, R_k), \sigma_h(R_k, \{a\})\}$.

HI-INTERCLASS-nC uses two joint rules to suggest assignments, the descending rule and the ascending rule, which must be used together. Each of these rules selects only one class for possible assignment of an alternative.

Descending assignment rule: Set β and λ. Define the set of classes C^h and the representative subsets of alternatives $\{r_0, R_1, \ldots, R_M, r_{M+1}\}$.

- Compare a with R_k for $k = M, \ldots, 0$, up to the first value, k, such that $aS_h(\beta)R_k$.
- For $k = M$, select C_M as a possible category to assign a.
- For $0 < k < M$, if $i_h(\{a\}, R_k) \geq i_h(\{a\}, R_{k+1})$, then select C_k as a possible category to assign a;

otherwise select C_{k+1}.

- For $k = 0$, select C_1 as a possible category to assign a.

Ascending allocation rule: Set β and λ. Define the set of classes C^h and the representative subsets of alternatives $\{r_0, R_1, \ldots, R_M, r_{M+1}\}$.

- Compare a with R_k for $k = 1, \ldots, M+1$, up to the first value, k, such that $R_k S_h(\beta) a$.
- For $k = 1$, select C_1 as a possible category to assign a.
- For $1 < k < M+1$, if $i_h(\{a\}, R_k) \geq i_h(\{a\}, R_{k-1})$, then select C_k as a possible category to assign a; otherwise select C_{k-1}.

For $k = M + 1$, select C_M as a possible category to assign a.

Results

The proposed methodology allows us to discern between the different levels of security, thus facilitating the classification of each city into one of the four predefined categories: High Security, Moderate Security, Low Security and Critical Insecurity. These classes are described below:

1. Class A - High Security: Cities that exhibit the lowest levels of crime and violence. These cities have effective surveillance systems, rapid response from authorities and low rates of reported crime. Furthermore, they could have high levels of citizen satisfaction with public safety (the evaluation of this assertion is outside the scope of this work).
2. Class B - Moderate Security: Cities with a moderate level of both crime and violence. They maintain workable security systems, but one might expect some difficulties regarding petty criminal activity or even isolated incidents of violence. Varied perception of security may be maintained in such cities; however, they are largely manageable.
3. Class C - Low Security: Cities in which the levels of crime and violence are highly evident. They can be continuously confronted with proble ms of safety, such as high rates of violent and property crimes. The effectiveness of the responses to security is often patchy, while the public perception of security is generally low.
4. Class D - Critical Insecurity: Cities with high levels of violence and crime, including frequent violent crimes and other serious security problems. These cities need urgent interventions and could well be under surveillance or direct support from the federal government or international organizations because of their critical situation.

For the criterion "social prevention of violence and crime" ($g_{2,2}$), the classes considered are: High Performance, Average Performance, Low Performance, Terrible Performance.

Additionally, the policymaker is interested in evaluating capital cities in terms of:

- public safety and the prevention capacity of capital cities,
- the incidence of high-impact crimes,
- the incidence of medium impact crimes,
- the incidence of low-impact crimes,
- social prevention measures for violence and crime.

In this section, we first detail the parameter values determined by the policymakers and, later, describe the results of assigning the capital cities to the mentioned classes.

Parameter values found

As stated above, for each elementary criterion g_i that belong to a non-elementary criterion g_h, a weight that symbolizes its relative importance is represented by w_{ih}. For simplicity, we will simply use w_i from now on. The weights are assumed to be positive and normalized, that is, $\sum w_i = 1$ for the direct subcriteria of each non-elementary criterion and $w_i \geq 0$ for all non-elementary criteria. The deck of cards technique was used to obtain the weights of the subcriteria of each non-elementary criterion (Corrente et al., 2017; Figueira & Roy, 2002). The results obtained are shown in Table 4.

Table 4. Weights of elementary and non-elementary criteria obtained with the "deck of cards" method

					g_0						
			g_1							g_2	
			0.5							0.5	
	$g_{1.1}$		$g_{1.2}$			$g_{1.3}$		$g_{2.1}$		$g_{2.2}$	
	0.398		0.149			0.156		0.05		0.241	
$g_{1,1,}$	$g_{1,1,}$	$g_{1,1,}$	$g_{1,2,}$	$g_{1,2,}$	$g_{1,3,}$	$g_{1,3,}$	$g_{1,3,}$	$g_{2,1,1}$	$g_{2,2,}$	$g_{2,2,}$	$g_{2,2,}$
0.3	0.3	0.3	0.7	0.2	0.3	0.6	0.0	1.00	0.3	0.2	0.3

For each elementary criterion g_i, the thresholds of indifference q_i, preference p_i and veto v_i can be specified (see Subsection 2.5). The indifference threshold is the maximum difference between the performances of alternatives a and b in g_i that is compatible with their indifference in g_i; the preference threshold is the minimum difference between the actions of a and b in g_i that is compatible with the preference of one over the other in g_i; the veto threshold represents the maximum difference between the performances of b over a in g_i that is incompatible with the outranking of *a* over. For consistency purposes, $q_i < p_i < v_i$. Table 5 presents the indifference and preference thresholds for each criterion provided by the policymakers. In this work, the veto threshold v_i is null for all criteria. Take, for example, the comparison of cities A_1 and A_{29} from the perspective of the Murders criterion; in this case, $g_{1,1,1}(A_1) = 51.4$ and $g_{1,1,1}(A_{29}) = 42.61$ (see Table 1). Since $q_{1,1,1} = 6.558$ $q_{1,1,1} = 6.558$ and $p_{1,1,1} = 9.837$ $p_{1,1,1} = 9.837$ (see Table 4), then $q_{1,1,1} < |g_{1,1,1}(A_1) - g_{1,1,1}(A_{29})| = 8.79 \le p_{1,1,1}$. Therefore, A_1 is weakly preferred to A_{29} from the perspective of the Murders criterion; that is, $(A_1, A_{29}) \in C(A_1 Q_{1,1,1} A_{29})$.

Table 5. Indifference and preference thresholds used by the interval-based hierarchical outranking approach

Code	Elementary criterion	Indifference	Preference
$g_{1,1,1}$	Homicides	6,558	9,837
$g_{1,1,2}$	Kidnappings	0.153	0.229
$g_{1,1,3}$	Violations	3,551	5,326
$g_{1,2,1}$	Property Crimes	51,819	77,729
$g_{1,2,2}$	Injuries	33,725	50,588
$g_{1,3,1}$	Common Theft	91,471	137,207
$g_{1,3,2}$	Bank robberies	0.049	0.748
$g_{1,3,3}$	Other Crimes	124,461	186,691
$g_{2,1,1}$	Strengthening Performance for Public Safety	429561.5	644342.3
$g_{2,2,1}$	Perception of Insecurity	6.32	9.48
$g_{2,2,2}$	Unemployment rate	0.336	0.504
$g_{2,2,3}$	Marginalization	0.029	0.044

As stated in Subsection 2.5, the set of reference profiles is given by $\{r_0, R_1, \ldots, R_M, r_{M+1}\}$, where each of these was defined by the policymaker according to the performance matrix of the alternatives (Table 3) as follows. R_2 to R_4, each containing a single profile, were defined using quartiles 3 to 1 (except in the case of $g_{2,1,1}$, which is a maximizing criterion and where quartiles 1 to 3 were used) of the corresponding column of Table 3 (for example, $g_{1,1,1}(r_{2,1})$ is the 3rd quartile of the $g_{1,1,1}$ column of Table 3, $g_{1,1,1}(r_{3,1})$ is quartile 2, $g_{1,1,1}(r_{4,1})$ is quartile 1, and so on). r_0 and r_5 were defined using the maximum and minimum of the corresponding columns of this table, respectively (minimum and maximum in the case of $g_{2,1,1}$). For its part, R_1 was defined based on the average between r_0 and $r_{2.1}$ (for example, $g_{1,1,1}(r_{1,1})$ is the average between $g_{1,1,1}(r_0)$ and $g_{1,1,1}(r_{2,1})$). Table 6 shows the profiles.

Table 6. Profiles considered by interval-based hierarchical outranking approach

	r_0	$r_{1,1}$	$r_{2,1}$	$r_{3,1}$	$r_{4,1}$	r_5
$g_{1,1,1}$	69.76	57.36	44.95	27.34	12.16	6.63
$g_{1,1,2}$	4.01	2.48	0.95	0.47	0.18	0
$g_{1,1,3}$	39.8	34.7	29.6	16.37	11.85	0.8
$g_{1,2,1}$	960.22	691.1	421.99	310.11	162.89	19.38
$g_{1,2,2}$	471.99	363.47	254.95	163.61	86.32	16.32
$g_{1,3,1}$	5564.79	3047.92	531.05	222.33	73.69	23.58
$g_{1,3,2}$	6.04	3.15	0.25	0	0	0
$g_{1,3,3}$	9328.7	5096.14	863.58	525.19	241.27	29.58
$g_{2,1,1}$	1184406	1936284	268816	3543654	4835969	10007409
$g_{2,2,1}$	87.7	83.2	78.7	64.7	47.1	24.6
$g_{2,2,2}$	7.89	6.75	5.61	4.81	3.93	2.4
$g_{2,2,3}$	-0.58	-0.85	-1.13	-1.24	-1.28	-1.39

Evaluation of capitals from a global perspective (public security and prevention capacity)

The ordinal classification of the capital cities carried out by the interval-based hierarchical outranking approach from a general criterion perspective and according to the preferences expressed by the policymaker is shown in Table 7.

Table 7. Ordinal classification of the capital cities from the general perspective of public security

Code	Lowest class	Highest class	Code	Lowest class	Highest class
A_1	*C*	*C*	A_{17}	*C*	*C*
A_2	*C*	*B*	A_{18}	*C*	*C*
A_3	*A*	*A*	A_{19}	*D*	*B*
A_4	*C*	*C*	A_{20}	*C*	*A*
A_5	*C*	*C*	A_{21}	*C*	*B*
A_6	*D*	*C*	A_{22}	*B*	*B*
A_7	*C*	*B*	A_{23}	*A*	*A*
A_8	*B*	*B*	A_{24}	*C*	*C*
A_9	*B*	*A*	A_{25}	*B*	*A*
A_{10}	*B*	*B*	A_{26}	*A*	*A*
A_{11}	*D*	*B*	A_{27}	*C*	*B*
A_{12}	*B*	*A*	A_{28}	*C*	*A*
A_{13}	*A*	*A*	A_{29}	*C*	*B*
A_{14}	*A*	*A*	A_{30}	*B*	*B*
A_{15}	*B*	*B*	A_{31}	*D*	*B*
A_{16}	*B*	*B*			

The dual assessment, which assigns two classes to each capital, reflects a more nuanced and complex perspective that considers different aspects and factors of public safety and is a feature of MCDA's ordinal classification approaches, particularly of the procedure described in Subsection 2.6. Its justification lies in the fact that, sometimes, the information is not consistent with a precise assignment of alternatives to classes. This causes such approaches, instead of forcing inconsistent recommendations, to provide a range of classes to which each alternative can belong. This may represent a step in the decision process that reduces the cognitive work of the decision maker. In case the decision maker does not agree to accept the recommendation as a final solution, it is recommended to carry out additional steps, in which there are two main complementary options: i) adjust the preferences of the decision maker by making changes to the parameters preferably, and ii) collect new information that allows more accurate impact values of alternatives on the criteria.

The classification of Mexican capitals in terms of security reveals a diverse panorama regarding the security situation in each city.

Discussion and conclusions

In this study, the safety of Mexico's capital cities was evaluated using an interval-based hierarchical outranking approach (Fernández et al., 2022). This evaluation allowed us to categorize the cities in four classes of security: High Security, Moderate Security, Low Security, and Critical Insecurity , providing nuanced views and representing the complexity of urban security challenges from different and complementary viewpoints in Mexico: general public safety and prevention capability, incidence of high-impact crimes, incidence of medium-impact crimes, incidence of low-impact crimes, and social violence and crime-preventing measures.

From a general perspective, the cities classified under High Security showed low rates for both violent and non-violent crimes, such as homicides, kidnappings, or even property crimes. This reflects good management in public safety and effective policies that prevent crimes. In comparison with other classes of cities, which are classified as lower, these cities have invested more in resources that pertain to public security. This would suggest that appropriateness in resource allocation is what is needed for low levels of crime. It is this level of safety that contributes to the immediate safety of the citizens and the overall goals of environmental, cultural, economic, and social sustainability, guaranteeing stability and prosperity in a community. On the other hand, the cities that fell into the category of Critical Insecurity indicated high crime rates in all the criteria studied. This evidences the critical need for governmental interventions in reforms of security strategies, improvement of coordination among different security forces, and more transparency and accountability in the institutions of public security.

One of the most significant findings that comes out of this research is the strong evidence indicating that investment in security seems positively correlated with perceived insecurity. Higher-ranked cities not only invest more in security but also have lower perceived rates of insecurity, signaling the relevance that might be attached to public perceptions in the assessment of the efficiency of security policies. This will also show the wider ramifications of security on social and economic stability. Additionally, the fact that high turnovers characterize the officials appointed to key positions in the security agencies of relatively insecure cities indicates that the long-term effectiveness of any security policy requires accompanying institutional stability. Lack of continuity would result in a loss of accumulated knowledge and experience that normally should translate into inconsistent implementation of policies and strategies regarding sustainability of security.

Recommendations:

1. Strengthening institutions. This should involve

stabilizing the leadership structures in security agencies and building institutional capacities for efficiently planning and executing security strategies. These measures can be obtained through periodic training and the development of more appealing and secure career profiles for public security professionals.

2. Investment in technology and resources: Growing investment in sophisticated security technology and the infrastructure that will be required to sustainably support that technology seems to enable cities to enhance their surveillance and rapid response and to conduct enhanced data analysis for preventing crimes. Doing this offers high support for sustainable development through ensuring safer environments within which economic activities and social interactions can take place.
3. Crime prevention policies should not only target the phenomena of crime but also address root causes that result in such criminality, like marginalization and unemployment. They are to include policies on education and employment, particularly for youths who are at risk. In this respect, cities can be made more inclusive and equitable, and these are basic precepts wherein sustainable cultural and economic growth prospers.
4. Interjurisdictional cooperation: Encourage increased intergovernmental cooperation, coordination, and collaboration between various levels and jurisdictions to more comprehensively address the issue of crime but particularly where organized crime is at its greatest. This can lead to better use of resources and a greater collective impact on public safety, thereby enhancing overall sustainability.
5. Continuous monitoring and evaluation: Ensure a robust monitoring and evaluation system to periodically review the effectiveness of security policies and make adjustments where necessary.

Such findings can be very useful to both state and federal political agendas in Mexico; but the proposed methodology can be applied elsewhere, since public security is a latent concern worldwide. Identifying the cities based on their security levels and then classifying them enables the policymaker to direct resources and efforts in an altogether more informed way. In this way, it helps to address defects in laggard cities while strengthening and maintaining the levels in already performing cities.

For further research, going deeper in the understanding and enhancement of public safety in capital cities, the set of evaluated criteria could be extended, incorporating variables such as judicial effectiveness and corruption. The longitudinal analyses will make it possible to comprehend temporal developments in security; comparisons with similar international contexts could be carried out. Furthermore, developing predictive models of security would contribute to knowing in advance changes that may occur, as well as carrying out preventive planning. These include evaluating the tangible effect of various security policies to ascertain which ones work best, how citizen involvement in security affects overall policy, and what the consequences are of integrating more advanced technologies, such as artificial intelligence, into the urban security strategies. We believe that such approaches will provide useful lessons to be used in the formulation of more effective policies and strategies at the local and national levels, thereby serving the greater cause of environmental, cultural, economic, and social sustainability.

Author contributions

Carlos Tolentino: Conceptualization, Methodology, validation, formal analysis, writing—review and editing, supervision. **Eyrán Díaz–Gurrola:** Methodology, formal analysis, investigation, data curation. **Xochitl Segura Lozano:** Software, validation, writing—original draft preparation. **Juan Antonio Granados–Montelongo:** Software, writing—review and editing, visualization. **José Daniel Corona–Flores:** writing—review and editing, visualization. **Juan Antonio Álvarez–Gaona:** writing—review and editing, visualization

Conflicts of interest

None.

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