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Smart Cities Maturity Model—A Multicriteria Approach

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Abstract: The concept of smart cities has gained relevance over the past few years. Public managers have been planning investments to turn their cities into smart cities. Maturity models can help managers to monitor the performance of urban indicators; however, these maturity models are not always capable of meeting their proposed goals. In this sense, this research aims to develop a maturity model that ranks the "smartness" of a city based on social and technological indicators. The Smart Cities Maturity Model (MMSC) variables were extracted from ISO's 37153:2017, 37120:2018, 37107:2019. The MMSC is structured on a hybrid TOPSIS multicriteria decision-making method. In this paper, we modified TOPSIS and used it to generate a synthetic indicator, called smart index, that designates the level of maturity of a real city. For this change to be possible, we fixed some alternatives and changed the positive ideal and negative ideal solution. The methodology is proven to be very efficient in measuring the smart city maturity level, and it can be easily adapted for the upcoming ISOs.

Keywords: smart cities; maturity model; TOPSIS; index

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1. Introduction

Approximately 55% of the world's population lives in urban areas, and this number is estimated to grow in the upcoming years [1]. This population increase is often disorderly, mainly in underdeveloped or developing countries, and has negative consequences for urban centers, especially related to health, safety, education, and urban mobility [2–5], leaving citizens vulnerable. Urban planning is the best way to solve such problems, since it aims to balance population needs with policies promoting efficient development [6,7]. In this process, emerging smart cities aim to identify the needs of people with a strategic focus on improving the quality of life.

The term smart cities can be defined as cities that promote energy efficiency, renewable energy, green mobility, and technological development, encouraging the exploration of knowledge management in urban environments [8–10]. Within its concept, smart actions provide the population with better quality of life through the growing process of innovation in their environment [11,12]. Smart cities seek to promote information and knowledge of the city for more effective management. Thus, managers become aware of the importance of integrating data between health, public security, education, and transport systems [13,14]; thus using them in a way to minimize the costs and waste that urban life generates, in terms of wellbeing and inclusion [15–19]. A smart city is the result of the implementation of advanced technological solutions for different infrastructures and urban activities such as services, business, transport, communication, water, and energy [20–22]. However, cities are considered smart when their technology becomes able to optimize the use of limited resources, assisting the main urban systems [23–26]. Several organizations have started a process of developing standards, specifications, and characteristics for smart cities [27,28]. Smart city solutions must play an important role supporting cities in achieving sustainable development goals (SDGs) [29–31], hence helping stakeholders to monitor the state and managing progress toward achieving the SDGs [32].

Improving the quality of life in cities is necessary; however, not all cities are smart and it is challenging to implement. Although several cities in the world are adhering to the smart city concept, there are no standards in the practices to identify the set of characteristics and processes that make a city smart, or in which level of performance it fits. The question then arises: How do we determine whether the smart practices adopted by a given city are capable of making it a smart city? In other words, how do we measure the smart performance of a city, given its local needs? In this way, it becomes relevant to develop a maturity model that is capable of embedding the specific characteristics of a city that wants to monitor its "smartness" and sustainable performance.

There is a range of studies in the literature that address maturity models [33–35] and focus on structures that measure the smartness of a city [36,37]. Torrinha and Machado [36] identifed a maturity model for smart cities and evaluated it, highlighting that the existing models, although meeting the need to assess the current state of a city, do not allow guidelines for progression along with the maturity levels. Cledou et al. [38] proposed taxonomy on intelligent mobility services. Sharifi [39] analyzed thirty-four tools to measure the performance of a smart city in order to identify its strengths and weaknesses in terms of content, structure, and procedures. Vidiasova et al. [40] evaluated the results of benchmarking worldwide practices in twenty smart cities and sought to determine the most successful cases that may be of interest for better urban development. Firmansyah et al. [41] used a participatory modeling approach to create interrelation maps with 52 factors (or concepts) connected by 98 links extracted from a systematic review carried out by the authors, transforming intuitive characterizations into numbers through diffuse logic. Warnecke et al. [42] provided a tool for evaluating the performance of smart cities such as focusing on urban mobility, monitoring development progress, and determining their competitive position through benchmarking.

In this process, the use of indicators helps cities to set goals and monitor their performance over time. These indicators were standardized by ISO 37120:2018 [43], created in 2014 and updated in 2018, being the first international standardization of standards created with a set of indicators to guide and measure municipal services performance and quality of life. The ISO 37120:2018 is based on a set of indicators focusing on guiding and measuring the performance of municipal services and quality of life. It is composed of 19 dimensions, subdivided into 111 indicators. The dimensions are economy, education, energy, environment and climate change, finance, governance, health, housing, social and population conditions, recreation, security, solid waste, sport and culture, telecommunications, transportation, urban/local agriculture and food security,urban planning, wastewater, and water. Currently, smart city assessment models focus on generating a ranking to classify cities, rather than focusing on the performance of the indicators. As a consequence, there are flawed assessment models that do not allow the identification of points for improvement, only generating ranking but not providing an action plan for decision-making that can improve a city's intelligence levels [44]. As far as it was possible to carry out our research, we did not find similar works to the proposed one. It is an exclusive work with a academic and social contribution, and it makes it possible to identify the maturity and the development of an action plan focused on the city's weaknesses, allowing the implementation of focal projects and enabling agility in actions to improve the quality of life of the population.

In order to provide standardized metrics for smart cities analysis, the World Council on City Data (WCCD) and the Global Cities Registry developed the first certification system based on ISO 37120. Currently, the WCCD Global Cities Registry has 103 cities certified based on ISO 37120. In addition to the WCCD, there are studies that present structures to identify the level of smartness of a city, although it is not characterized as a maturity model (MM), being only a structure that evaluates and ranks the analyzed cities, using a set of smart indicators. Several studies have been carried out using multicriteria methods for the construction of indicators, which can be elementary methods such as SAW, WPM, and AHP [45–51]; utility value-based methods such as MAUT, MAVT, SMART, and MACBETH [52–68]; methods based on peer comparison such as ELECTRE and PROMETHEE [69–74]; methods based on data envelopment analysis such as MCDM-DEA and BoD [75–86]; and methods based on distance functions such as the goal programming method, commitment programming methods, TOPSIS, and GRA [87–104]. Not all of these methods are characterized as noncompensatory.

The research gap of this study is structured on a maturity model capable of quantitatively evaluating the elements defined as "smartness" for a city. Thus, the proposed model is based on an evaluation process that allows the development of a smart city, helping it to achieve its objectives.

Therefore, based on these premises, the main goals of this work are the following:

- Present a maturity model focused on smart cities.
- Understand the maturity levels that characterize a city as smart. This stage was supported by the five reference levels presented in the International Organization for Standardization (ISO) ISO 37153:2017—Smart community infrastructures—Maturity model for assessment and improvement and ISO 37107:2019—Sustainable cities and communities—Maturity model for smart sustainable communities.
- Use the proposed modified methodology of the TOPSIS method—Technique for Order Preference by Similarity to Ideal Solution, where, unlike the original function of the method, which is to rank the alternatives, here it was used to generate a synthetic indicator called smart index.
- Present the application of the maturity model in the city of London/UK, currently considered the most intelligent city in the world by the IESE—Business Schools Center for Globalization and Strategy ranking.

In this sense, this work is organized as follows: Section 2 presents the state of art regarding existing research to measure the maturity of smart cities. In the sequence, Section 3 presents the methodology and the variables used to determine the maturity of smart cities. The results of the application of the proposed model are in Section 4. Finally, Section 5 presents the main conclusions of the research. Figure 1 shows the conceptual diagram of the study.

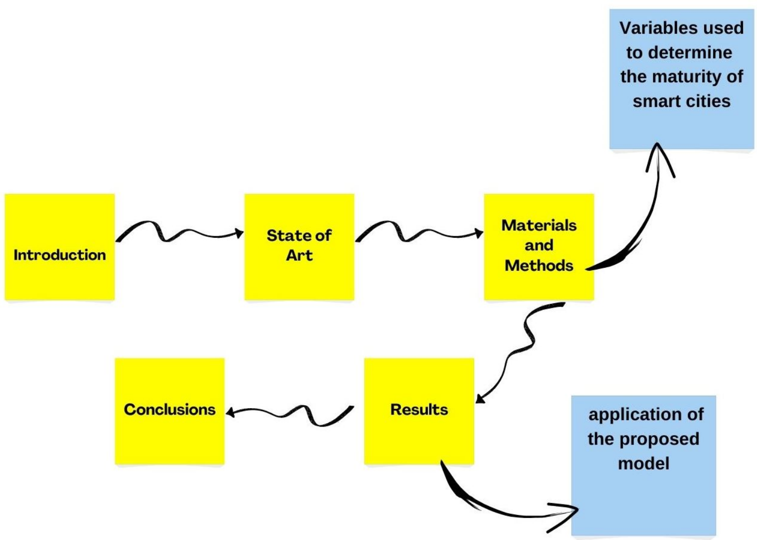

Figure 1. Conceptual diagram.

2. State of the Art

A smart city is considered the result of a learning process based on local evidence, which places the individual at the center of urban politics. To this end, some researchers detected three different ways of characterizing a city as smart based on the context of urban and economic development [18], its strategic planning [105], and, finally, in the context of technologies, people, and institutions in an aggregate form [106].

The smart city concept is guided by characteristics of smartness, being characteristics of intelligence applied to the urban environment, following international standards. Several organizations have started a process of developing standards, specifications, and characteristics for smart cities. This is to clarify domains of a smart city and how they are treated in the performance-measuring process of the smartness of an urban environment [27,28]. Smart city solutions must play an important role supporting cities in achieving sustainable development goals (SDGs) [29,30] by helping stakeholders to monitor the state, and managing progress towards achieving the SDGs [32].

ISO 37122:2019 was developed based on ISO 37120:2018. ISO 37120:2018 deals with indicators for smart cities, and ISO 37123:2019 deals with indicators for resilient cities [43]. Currently, there are several international standards for city indicators that are relevant for the evaluation and reporting of smart and sustainable cities.

In order to provide standardized metrics for smart cities' analysis, the World Council on City Data (WCCD) and the Global Cities Registry developed the first certification system based on ISO 37120. WCCD leads the development of standards to create smart, sustainable, and resilient cities, which must follow the standards set out by ISO 37120 [107]. These indicators have been tested by the GlobalCity Indicators Facility in more than 250 member cities worldwide. The standard is a measurement model for cities that want to become smart and sustainable.

Currently, the WCCD Global Cities Registry has 103 cities certified based on ISO 37120. In 2018, the following cities obtained a platinum certification level: Piedras Negras (Mexico), Welland (Canada), Mississauga (Canada), Taipei (Taiwan), Aalter (Belgium), Tainan City (Taiwan), Brisbane (Australia), Whitby (Canada), Oakville (Canada), Quebec City (Canada), and Kópavogur (Iceland) [108]. In 2019, the platinum cities were Guadalupe (Mexico), Guelph (Canada), Mississauga (Canada), Whitby (Canada), and Brisbane (Australia).

In addition to the WCCD, there are studies that present structures to identify the level of smartness of a city, although it is not characterized as a maturity model (MM), being only a structure that evaluates and ranks the analyzed cities using a set of smart indicators. In these studies, the IDC Smart City Maturity Model (IDC SCMM) developed by Clarke [109] is an MM aimed at smart cities, which makes an assessment of the current state as a planning tool. The model does not provide any calculation measures and also does not present its composition of indicators.

The Maturity Model to Measure and Compare Inequality in Brazilian Cities (Br-SCMM), proposed by Afonso et al. [110], offers a tool to identify areas and objectives to be strategically planned towards a smart city paradigm. Br-SCMM uses only the Z-score to define the value of the indicator and, given the values established by the statistical method, it incorporates them in the established levels of maturity, with five levels of maturity.

The Smart City Maturity Model, developed by Sustainability Outlook (SO SCMM) and proposed by Mani and Banerjee [111], provides a comprehensive set of indicators based on ISO 37120. This maturity model consists of an evaluation framework and a solution framework. The assessment framework helps a city or a state assess the conditions of its social, physical, and technological developments, identifying its readiness for the implementation of smart city solutions. As a form of calculation, it presents a structured ranking, based on the number of computed indicators, and determines the level of maturity of the city.

Considering its purpose, the IDC SCMM, Br-SCMM, and SO SCMM are models that focus on the assessment of the current state of the city. Although Br-SCMM and SO SCMM fulfill their goal of allowing an assessment of the city by providing measurements, even if only for the first level, IDCSCMM fails to do so. Despite its intention to assess the current state of a city, the model does not provide measures to achieve such a proposal, nor does it guide how to do so.

Góngora and Bernal [112] presented a validation of the maturity model for information technology management in smart cities. The model proposed for Colombian cities is still in the testing phase, and it did not present its calculation steps. Anand et al. [113] used the fuzzy-AHP technique to identify the importance of sustainability-oriented indicators for a smart city. They also used data envelopment analysis (DEA) to determine the efficiency of each indicator. It allowed them to identify which sustainability indicators have poor results, thus focusing on improving the performance of these indicators. Anthopoulos and Giannakidis [114] conducted a study that focused on standardizing the process of formulating public policies in smart cities. It used the task-based modeling method to map the process of formulating policies related to the public planning of a city and identified the groups of criteria. Later, the study used the Promethee multicriteria technique to identify the underperforming scenarios. In addition, it identified nine cities in the world [38,115,116] (Curitiba, Seattle, Surrey, Dubai, Songdo, Amsterdam, Barcelona, Copenhagen, Vienna) that have already been recognized as cities that stand out in some of the six dimensions [105] for a smart city.

These studies show that the present structures for monitoring the smartness of a city are mostly supported by ISO indicators, but these structures are not clear regarding their calculations and are flawed for presenting proposals for improvements in smart dimensions, which makes the structures complex in their replication.

Several aspects must be taken into consideration when choosing the indicators to measure urban characteristics, such as the relevance of the indicator for the region studied, the possibility of measuring the trend over time, and its relationship among the indicators, since it should assist in the development of strategic decision-making in the analyzed city [117,118]. In the combination of the different indicators for the composition of a synthetic indicator [119], a series of techniques can be used in the stages of standardization, weighting, and aggregation.

In this context, several studies have been carried out using multicriteria methods for the construction of indicators, which can be elementary methods such as SAW, WPM, and AHP [45–51]; utility-value-based methods such as MAUT, MAVT, SMART, and MACBETH [52–68]; methods based on peer comparison such as ELECTRE and PROMETHEE [69–74]; methods based on data envelopment analysis such as MCDM-DEA and BoD [75–86]; and methods based on distance functions such as the goal programming method, commitment programming methods, TOPSIS, and GRA [87–104]. Not all of these methods are characterized as noncompensatory. The SAW, UTA, SMART, DEA, and TOPSIS methods are characterized by total compensation between the criteria; the methods MAUT and MAVT adopt multiplicative functions in their mathematical composition, limiting the compensation between the criteria; and the ELECTRE and PROMETHEE methods are characterized as noncompensatory methods [120].

3. Materials and Methods

The first stage of the proposed model refers to the definition of the levels of maturity that characterize a city as smart. This stage was supported by the five reference levels presented in ISO 37153:2017—Smart community infrastructures—Maturity model for assessment and improvement and ISO 37107:2019 Sustainable cities and communities—Maturity model for smart sustainable communities [121,122].

The characterization of the maturity levels that compose the MMSC was based on the levels proposed by ISO 37153:2017 and ISO 37107:2019. The levels of the MMSC are:

- Level 1—No smartness infrastructure working;
- Level 2—Smartness working but not meeting future needs;
- Level 3—Smartness meets current needs;
- Level 4—Smartness partially initiated for future needs;
- Level 5—Smartness continuously improving to meet future needs.

It is noteworthy that ISO 37153:2017 and ISO 37107:2019, when defining the performance of the maturity levels, are presented qualitatively and each level assumes that the requirements of the previous levels have been met. Thus, for the levels to be measured quantitatively, we will use the system of standards and classification for urban sustainability indicators proposed by Wang and Xu [123] and Li et al. [124]. Table 1 lists the smart axis/dimension classification criteria proposed by these authors.

Table 1. Value of maturity levels [123,124].

Level	Value	Qualitative Evaluation
5	>0.91	Great
4	0.90–0.76	Good
3	0.75–0.51	Moderate
2	0.50–0.26	Low
1	<0.25	Poor

The model variables will be considered here as "smart axes". The "smart axes" encloses the "smart dimensions", which, in turn, include the "smart indicators" group. The smart axes (E_s) represent the characteristics that a smart city should have. The smart dimensions (D_s) define the theme of each indicator, and the smart indicators (I_s) measure the smartness performance of a city.

The first variables to be defined in the proposed model are the smart axes. Some authors have systematized the smart cities approach in axes that guide the sets of indicators, which will be part of the smart city assessment tools. Giffinger et al. [105] conceptualized six axes for a smart city, which are smart economy, smart people, smart living, smart governance, smart mobility, and smart environment. Subsequently, the evaluation alternatives were defined as utopian city (A^+), reference city (A_R), real city (A), and limit city (A_0). For the six smart axes, based on ISO 37120:2018 (Sustainable cities and communities—Indicators for city services and quality of life), we identified 19 smart dimensions, which in turn have 111 indicators that will compose the MMSC. ISO 37120:2018 presents 19 dimensions for smart cities, which aim to guide and evaluate the performance management of urban activities. This standard considers sustainability as its general principle and the "smart city" as a guiding concept in the development of urban spaces.

Therefore, for each dimension, we defined respective indicators, as prescribed by ISO 37120:2018. Thus, the study contemplates the 6 smart axes conceptualized by Giffinger et al. [105]; the 19 smart dimensions and 111 smart indicators conceptualized by ISO 37120:2018; and the levels of maturity conceptualized by ISO 37153:2017 and ISO 37107:2019. Figure 2 presents the hierarchical structure of the MMSC.

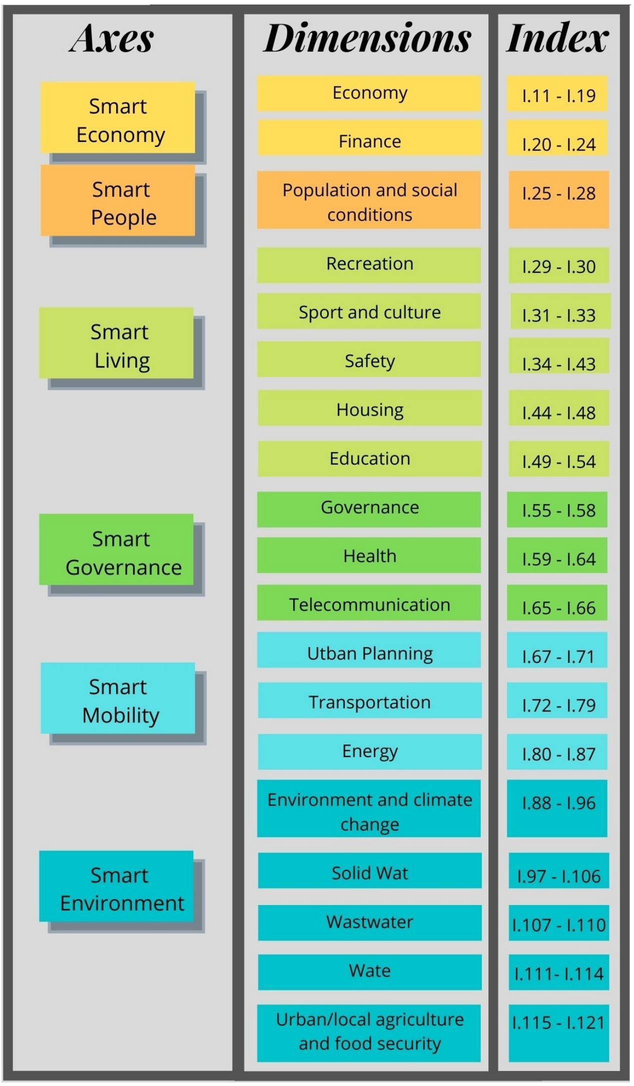

Figure 2. Hierarchical structure of the problem.

Model Methodology

To achieve the study goal, we developed a methodology for a maturity model for smart cities. The multicriteria method Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) used in this step was proposed by Tzeng and Huang [125] and has been used in several works; it is one of the most widely used multicriteria methods [126], and it stands out for looking for the alternative that is furthest from the negative ideal solution and closer to the positive ideal solution. In this study, the TOPSIS method was structured as a mathematical instrument for measuring the MMSC smartness in the health area [127,128], environment and sustainability [129–138], technology [139–144], and urban spaces and developments [145–149], among many others in the engineering fields [150–162].

The method starts with the construction of the decision matrix with the data of each indicator for each city, followed by the normalization process, by using the following equation:

$$r_{ij} = x_{ij} / \sum_{i=1}^{m} x_{ij} \tag{1}$$

where r_{ij} is between 0 and 1.

In the sequence, it is necessary to weigh the matrix. The v_{ij} elements of the weighted normalized matrix are calculated using the following equation:

$$v_{ij} = \omega_i \cdot r_{ij}, \qquad j = 1, \ldots, m; \quad i = 1, \ldots, n \tag{2}$$

With the normalized and weighted matrix, the next step is to determine the positive ideal (A^*) and negative ideal (A^-) solution using the following equations:

$$A^* = \{v_i^+, \ldots, v_n^+\} = \{(max_j v_{ij} \mid i \in B), (min_j v_{ij} \mid i \in C)\} \tag{3}$$

$$A^- = \{v_i^-, \ldots, v_n^-\} = \{(min_j v_{ij} \mid i \in B), (max_j v_{ij} \mid i \in C)\} \tag{4}$$

where B are the benefit (or maximization) criteria and C are the cost (or minimization) criteria.

In this methodology, we modified the TOPSIS method. We give the positive ideal solution the value of 1 for maximization criteria and 0 for minimization criteria, and for the negative ideal solution, maximizing criteria have a value of 0 and minimization criteria a value of 1. This change in method occurred to measure the maturity of the smart city.

Then, the method calculates the Euclidean distance between each alternative to the positive ideal solution (S^*) and the negative ideal solution (S^-), respectively, according to the following equations:

$$S_i^* = \sqrt{\sum_{j=1}^{n} \left(v_{ij} - v_j^*\right)^2} \tag{5}$$

$$S_i^- = \sqrt{\sum_{j=1}^{n} \left(v_{ij} - v_j^-\right)^2} \tag{6}$$

Finally, the last step of the method consists of determining the relative proximity of each alternative (C_i^*) tothe positive ideal solution, using the following equation:

$$C_i^* = \frac{S_i^-}{(S_i^* + S_i^-)} \tag{7}$$

From the values of the CC_i of each city, the smart index (I_{smart}) is calculated, which determines the maturity level of the real city, as shown in Equation (8).

$$I_{smart} = \frac{A_n}{A^+} \tag{8}$$

Note that in the proposed model, the axes, dimensions, and indicators have the same importance. The study proposed by Vavrek and Chovancová [163] reports that it is not possible to determine the weight of an extensive set of indicators (as in this case) using expert opinion; thus, the weights of the axes, dimensions, and indicators were defined by being equally distributed.

Unlike the original proposal of the TOPSIS method, the proposed model does not intend to generate a ranking among the alternatives (A_n). Here, the TOPSIS is used to generate a synthetic indicator that measures the maturity level of a city in the smart context. Therefore, the utopian city (A^+), reference city (A_R), and limit city (A_0) are fixed alternatives that will determine the maturity level of the real city (A).

4. Results

Application of the Maturity Model for Smart Cities

The Smart Cities Maturity Model (MMSC) was structured based on ISO 37153:2017, ISO 37107:2019, and ISO 37120:2018, which were tested using data from the city of London/UK. The British capital led the ranking of the IESE Business Schools Center for Globalization and Strategy for the year 2019.

The first step consists of applying the TOPSIS method. The weights (W) of the smart indicators are the same because when considering a smart city, all the variables that define it must be structured in an equal way, not compensating for the other variables. Thus, the decision matrix is first assembled with the 11 indicators (criteria) and the 4 alternatives: utopian city (A^+), reference city (A_R), limit city (A_0), and real city (A) (Table 2).

Table 2. Alternatives.

Code	City
A^+	Utopian
A_0	Limit
A_R	Reference
A	Real

The values of the utopian city indicators are utopian (in order of magnitude). The indicators of the reference city are represented by the best value among the most intelligent cities in the world according to IESE (London, New York, Amsterdam, Paris, and Reykjavík). Regarding the indicators of limit city, their values are represented by the minimum performance between London, New York, Amsterdam, Paris, and Reykjavík. Regarding the real city, the values of the London indicators were used.

The data referring to the indicators of the utopian city, limit city, reference city, and real city were extracted from the following databases: WCCD Global Cities Registry, Numbeo, The World Bank, Global SDG Indicators Database, World Health Organization.

After defining the values of each smart indicator and its respective alternative, the TOPSIS multicriteria method was applied. This method was used because it is quite widespread in the construction of synthetic indicators. For its use in this model, it was necessary to make a change in the method, and in the proposed model the alternatives utopian city, reference city, and limit city are fixed. Thus, they become fixed alternatives, since the focus is not to build a ranking, but, through the coefficient proximity to real city, generate a synthetic indicator that allows measuring its level of maturity.

Indicator values I.12, I.17, I.19, I.24, I.28, I.32, I.33, I.35, I.42, I.48, I.54, I.56, I.63, I.64, I.68, I.69, I.70, I.71, I.72, I.74, I.77, I.79, I.83, I.84, I.85, I.87, I.120, and I.121 were not found either, because they are not measured or the responsible authorities do not disclose them; thus, they were excluded from the analysis, but they should be used whenever available. Table 3 presents the initial decision matrix.

Table 3. Decision matrix.

Index	A^+	A_0	A_R	A (London)	Index	A^+	A_0	A_R	A (London)
I.11	0.0	6.0	2.8	2.8	I.66	345,000	114,000	129,000	129,000
I.13	1.0	0.0	1.0	1.0	I.67	860.0	4.0	700.0	13.5
I.14	0.0	1.0	0.0	0.1	I.73	502	109	480	480
I.15	100.0	0.0	9.3	9.3	I.75	64.7	0.0	1.2	1.2
I.16	100.0	0.0	86.5	86.5	I.76	0.0	100.0	3.0	3.0
I.18	920,000	450,000	515,811	515,811	I.78	12.0	162.0	20.0	162.0
I.20	0.0	3.0	0.0	0.0	I.80	1.0	10.0	2.1	5.1
I.21	0.0	25.0	0.2	0.2	I.81	1.0	0.0	0.8	0.8
I.22	1.0	0.0	0.3	0.3	I.82	1.0	0.0	1.0	1.0
I.23	0.0	50.0	31.0	30.6	I.86	0.0	168.0	24.0	4.0
I.25	0.0	2.0	0.0	0.1	I.88	0.0	125.0	25.0	0.1
I.26	0.0	2.0	0.0	0.0	I.89	0.0	250.0	50.0	50.0
I.27	0.0	31.0	27.0	26.8	I.90	0.0	0.1	0.0	0.7
I.29	24.0	5.0	18.0	18.0	I.91	1.0	0.0	0.3	0.3
I.30	40.0	5.0	22.0	14.0	I.92	0	1130	200	134
I.31	1000	0	676	676	I.93	0	800	20	14
I.34	1000	0.0	30.0	30.0	I.94	0	200	100	66
I.36	0.0	10.0	0.0	2.0	I.95	0.0	85.0	70.0	53.4
I.37	10000	10	635	635	I.97	1.0	0.0	1.0	1.0
I.38	0.0	30.0	1.2	0.8	I.98	1.0	0.0		1.0
I.39	10000.0	10.0	21.7	17.7	I.99	1.0	0.1	0.4	0.4
I.40	2.0	60.0	5.0	3.0	I.100	100	32	89	89
I.43	0.0	5.0	0.0	1.4	I.102	1.0	0.1	0.2	0.2
I.44	0.0	0.1	0.0	0.0	I.103	0.0	1.0	0.3	0.3
I.45	0.0	1.0	0.0	0.1	I.104	0.0	1.0	0.0	0.0
I.46	0	100,000	38	108	I.105	0.0	100.0	0.0	0.1
I.47	0.0	1.0	0.0	1.0	I.106	1.0	0.0	0.6	0.6
I.49	1.0	0.0	1.0	1.0	I.108	1.0	0.0	0.8	0.8
I.50	1.0	0.0	1.0	1.0	I.109	0.0	1.0	0.0	0.0
I.51	1.0	0.7	1.0	1.0	I.110	0.0	1.0	0.0	0.0
I.52	1.0	0.3	10.0	10.0	I.111	1.0	0.9	1.0	1.0
I.53	1.0	0.5	1.0	1.0	I.112	1.0	0.5	0.8	0.8
I.55	0.5	0.6	0.4	0.4	I.113	1.0	0.6	0.7	0.7
I.57	100.0	80.0	100.0	93.0	I.114	1.0	0.7	1.0	1.0
I.58	100.0	36.0	100.0	96.0	I.115	1.0	0.8	1.0	1.0
I.59	85.0	25.0	83.0	83.0	I.116	1.0	0.9	1.0	1.0
I.60	1870.0	0.0	650.0	650.0	I.117	107	0	110	110
I.61	1.0	0.0	0.5	0.5	I.118	1.0	0.1	0.2	0.2
I.62	0.0	1000.0	2.0	2.0	I.119	107	0	110	110
I.65	100,000	78,000	99,000	99,000					

Table 4 shows the weighted normalized decision matrix, obtained by the application of Equations (1) and (2).

For the definition of the positive ideal and negative ideal solutions, the values were set to 1 for maximization criteria and 0 for minimization criteria in the positive ideal solution, and for the negative ideal solution, the maximization criteria received a value of 0 and the minimization received the value of 1. Applying Equations (5) and (6), it was possible to calculate the positive ideal and negative ideal distances, as shown in Table 5.

Table 4. Normalized decision matrix.

Index	A^+	A_0	A_R	A (London)	Index r	A^+	A_0	A_R	A (London)
I.11	0.00	0.52	0.24	0.24	I.66	0.48	0.16	0.18	0.18
I.13	0.34	0.00	0.33	0.33	I.67	0.55	0.00	0.44	0.01
I.14	0.00	0.90	0.04	0.06	I.73	0.32	0.07	0.31	0.31
I.15	0.84	0.00	0.08	0.08	I.75	0.96	0.00	0.02	0.02
I.16	0.37	0.00	0.32	0.32	I.76	0.00	0.94	0.03	0.03
I.18	0.38	0.19	0.21	0.21	I.78	0.03	0.46	0.06	0.46
I.20	0.00	1.00	0.00	0.00	I.80	0.05	0.55	0.12	0.28
I.21	0.00	0.98	0.01	0.01	I.81	0.39	0.00	0.30	0.30
I.22	0.66	0.00	0.17	0.17	I.82	0.33	0.00	0.33	0.33
I.23	0.00	0.45	0.28	0.27	I.86	0.00	0.86	0.12	0.02
I.25	0.00	0.95	0.00	0.05	I.88	0.00	0.83	0.17	0.00
I.26	0.00	1.00	0.00	0.00	I.89	0.00	0.71	0.14	0.14
I.27	0.00	0.37	0.32	0.32	I.90	0.00	0.13	0.01	0.87
I.29	0.37	0.08	0.28	0.28	I.91	0.60	0.00	0.20	0.20
I.30	0.49	0.06	0.27	0.17	I.92	0.00	0.77	0.14	0.09
I.31	0.43	0.00	0.29	0.29	I.93	0.00	0.96	0.02	0.02
I.34	0.00	0.89	0.11	0.00	I.94	0.00	0.55	0.27	0.18
I.36	0.00	0.83	0.00	0.17	I.95	0.00	0.41	0.34	0.26
I.37	0.89	0.00	0.06	0.06	I.97	0.33	0.00	0.33	0.33
I.38	0.00	0.94	0.04	0.02	I.98	0.51	0.00	0.00	0.49
I.39	1.00	0.00	0.00	0.00	I.99	0.56	0.06	0.19	0.19
I.40	0.03	0.86	0.07	0.04	I.100	0.32	0.10	0.29	0.29
I.43	0.00	0.78	0.00	0.22	I.102	0.68	0.07	0.12	0.12
I.44	0.00	1.00	0.00	0.00	I.103	0.00	0.66	0.17	0.17
I.45	0.00	0.93	0.02	0.05	I.104	0.00	1.00	0.00	0.00
I.46	0.00	1.00	0.00	0.00	I.105	0.00	1.00	0.00	0.00
I.47	0.00	0.50	0.00	0.50	I.106	0.44	0.00	0.28	0.28
I.49	0.33	0.00	0.33	0.33	I.108	0.40	0.00	0.30	0.30
I.50	0.33	0.00	0.33	0.33	I.109	0.00	0.96	0.01	0.03
I.51	0.27	0.19	0.27	0.27	I.110	0.00	0.98	0.02	0.00
I.52	0.05	0.01	0.47	0.47	I.111	0.26	0.22	0.26	0.26
I.53	0.29	0.14	0.29	0.29	I.112	0.34	0.15	0.25	0.25
I.55	0.26	0.32	0.21	0.21	I.113	0.34	0.19	0.23	0.23
I.57	0.27	0.21	0.27	0.25	I.114	0.27	0.19	0.27	0.27
I.58	0.30	0.11	0.30	0.29	I.115	0.26	0.21	0.26	0.26
I.59	0.31	0.09	0.30	0.30	I.116	0.26	0.23	0.26	0.26
I.60	0.59	0.00	0.21	0.21	I.117	0.33	0.00	0.34	0.34
I.61	0.50	0.00	0.25	0.25	I.118	0.69	0.07	0.12	0.12
I.62	0.00	1.00	0.00	0.00	I.119	0.33	0.00	0.34	0.34
I.65	0.27	0.21	0.26	0.26					

Table 5. Positive and negative ideal distances.

Index	S^*				S^-				Index	S^*				S^-			
	A^+	A_0	A_R	A	A^+	A_0	A_R	A		A^+	A_0	A_R	A	A^+	A_0	A_R	A
I.11	0.0	0.5	0.2	0.2	−1.0	−0.5	−0.8	−0.8	I.66	−0.5	−0.8	−0.8	−0.8	0.5	0.2	0.2	0.2
I.13	−0.7	−1.0	−0.7	−0.7	0.3	0.0	0.3	0.3	I.67	−0.5	−1.0	−0.6	−1.0	0.5	0.0	0.4	0.0
I.14	−1.0	−0.1	−1.0	−0.9	0.0	0.9	0.0	0.1	I.73	−0.7	−0.9	−0.7	−0.7	0.3	0.1	0.3	0.3
I.15	−0.2	−1.0	−0.9	−0.9	0.8	0.0	0.1	0.1	I.75	0.0	−1.0	−1.0	−1.0	1.0	0.0	0.0	0.0
I.16	−0.6	−1.0	−0.7	−0.7	0.4	0.0	0.3	0.3	I.76	0.0	0.9	0.0	0.0	−1.0	−0.1	−1.0	−1.0
I.18	−0.6	−0.8	−0.8	−0.8	0.4	0.2	0.2	0.2	I.78	0.03	0.46	0.06	0.46	−0.97	−0.54	−0.94	−0.54
I.20	0.0	1.0	0.0	0.0	−1.0	0.0	−1.0	−1.0	I.80	−0.9	−0.5	−0.9	−0.7	0.1	0.5	0.1	0.3
I.21	0.0	1.0	0.0	0.0	−1.0	0.0	−1.0	−1.0	I.81	−0.6	−1.0	−0.7	−0.7	0.4	0.0	0.3	0.3
I.22	0.7	0.0	0.2	0.2	−0.3	−1.0	−0.8	−0.8	I.82	−0.7	−1.0	−0.7	−0.7	0.3	0.0	0.3	0.3
I.23	0.0	0.4	0.3	0.3	−1.0	−0.6	−0.7	−0.7	I.86	0.0	0.9	0.1	0.0	−1.0	−0.1	−0.9	−1.0
I.25	0.0	1.0	0.0	0.0	−1.0	0.0	−1.0	−1.0	I.88	0.0	0.8	0.2	0.0	−1.0	−0.2	−0.8	−1.0
I.26	0.0	1.0	0.0	0.0	−1.0	0.0	−1.0	−1.0	I.89	0.0	0.7	0.1	0.1	−1.0	−0.3	−0.9	−0.9
I.27	0.0	0.4	0.3	0.3	−1.0	−0.6	−0.7	−0.7	I.90	−1.0	−0.9	−1.0	−0.1	0.0	0.1	0.0	0.9
I.29	−0.6	−0.9	−0.7	−0.7	0.4	0.1	0.3	0.3	I.91	−0.4	−1.0	−0.8	−0.8	0.6	0.0	0.2	0.2
I.30	−0.5	−0.9	−0.7	−0.8	0.5	0.1	0.3	0.2	I.92	0.0	0.8	0.1	0.1	−1.0	−0.2	−0.9	−0.9
I.31	−0.6	−1.0	−0.7	−0.7	0.4	0.0	0.3	0.3	I.93	0.0	1.0	0.0	0.0	−1.0	0.0	−1.0	−1.0
I.34	−1.0	−0.1	−0.9	−1.0	0.0	0.9	0.1	0.0	I.94	0.0	0.5	0.3	0.2	−1.0	−0.5	−0.7	−0.8
I.36	0.0	0.8	0.0	0.2	−1.0	−0.2	−1.0	−0.8	I.95	0.0	0.4	0.3	0.3	−1.0	−0.6	−0.7	−0.7
I.37	−0.1	−1.0	−0.9	−0.9	0.9	0.0	0.1	0.1	I.97	−0.7	−1.0	−0.7	−0.7	0.3	0.0	0.3	0.3
I.38	0.0	0.9	0.0	0.0	−1.0	−0.1	−1.0	−1.0	I.98	−0.5	−1.0	−1.0	−0.5	0.5	0.0	0.0	0.5
I.39	0.0	−1.0	−1.0	−1.0	1.0	0.0	0.0	0.0	I.99	−0.4	−0.9	−0.8	−0.8	0.6	0.1	0.2	0.2
I.40	0.0	0.9	0.1	0.0	−1.0	−0.1	−0.9	−1.0	I.100	−0.7	−0.9	−0.7	−0.7	0.3	0.1	0.3	0.3
I.43	0.0	0.8	0.0	0.2	−1.0	−0.2	−1.0	−0.8	I.102	−0.3	−0.9	−0.9	−0.9	0.7	0.1	0.1	0.1
I.44	0.0	1.0	0.0	0.0	−1.0	0.0	−1.0	−1.0	I.103	0.0	0.7	0.2	0.2	−1.0	−0.3	−0.8	−0.8
I.45	0.0	0.9	0.0	0.0	−1.0	−0.1	−1.0	−1.0	I.104	0.0	1.0	0.0	0.0	−1.0	0.0	−1.0	−1.0
I.46	0.0	1.0	0.0	0.0	−1.0	0.0	−1.0	−1.0	I.105	0.0	1.0	0.0	0.0	−1.0	0.0	−1.0	−1.0
I.47	0.0	0.5	0.0	0.5	−1.0	−0.5	−1.0	−0.5	I.106	−0.6	−1.0	−0.7	−0.7	0.4	0.0	0.3	0.3
I.49	−0.7	−1.0	−0.7	−0.7	0.3	0.0	0.3	0.3	I.108	−0.6	−1.0	−0.7	−0.7	0.4	0.0	0.3	0.3
I.50	−0.7	−1.0	−0.7	−0.7	0.3	0.0	0.3	0.3	I.109	0.0	1.0	0.0	0.0	−1.0	0.0	−1.0	−1.0
I.51	−0.7	−0.8	−0.7	−0.7	0.3	0.2	0.3	0.3	I.110	0.0	1.0	0.0	0.0	−1.0	0.0	−1.0	−1.0
I.52	−1.0	−1.0	−0.5	−0.5	0.0	0.0	0.5	0.5	I.111	−0.7	−0.8	−0.7	−0.7	0.3	0.2	0.3	0.3
I.53	−0.7	−0.9	−0.7	−0.7	0.3	0.1	0.3	0.3	I.112	−0.7	−0.8	−0.7	−0.7	0.3	0.2	0.3	0.3
I.55	−0.7	−0.7	−0.8	−0.8	0.3	0.3	0.2	0.2	I.113	−0.7	−0.8	−0.8	−0.8	0.3	0.2	0.2	0.2
I.57	−0.7	−0.8	−0.7	−0.8	0.3	0.2	0.3	0.2	I.114	−0.7	−0.8	−0.7	−0.7	0.3	0.2	0.3	0.3
I.58	−0.7	−0.9	−0.7	−0.7	0.3	0.1	0.3	0.3	I.115	−0.7	−0.8	−0.7	−0.7	0.3	0.2	0.3	0.3
I.59	−0.7	−0.9	−0.7	−0.7	0.3	0.1	0.3	0.3	I.116	−0.7	−0.8	−0.7	−0.7	0.3	0.2	0.3	0.3
I.60	−0.4	−1.0	−0.8	−0.8	0.6	0.0	0.2	0.2	I.117	−0.7	−1.0	−0.7	−0.7	0.3	0.0	0.3	0.3
I.61	−0.5	−1.0	−0.8	−0.8	0.5	0.0	0.2	0.2	I.118	−0.3	−0.9	−0.9	−0.9	0.7	0.1	0.1	0.1
I.62	0.0	1.0	0.0	0.0	−1.0	0.0	−1.0	−1.0	I.119	−0.7	−1.0	−0.7	−0.7	0.3	0.0	0.3	0.3
I.65	−0.7	−0.8	−0.7	−0.7	0.3	0.2	0.3	0.3									

In the final step, the proximity coefficient CC_i was calculated by Equations (7) and (8). The CC_i defines the smart index that represents the cities maturity level. Table 6 show the values for this step.

Table 6. Classification.

City	S_i^*	S_i^-	C_i	Ranking	Smart Index
A^+	0.47	0.74	0.61	1	1.00
A_0	0.89	0.20	0.18	4	0.29
A_R	0.60	0.62	0.51	2	0.83
A (London)	0.59	0.61	0.51	3	0.82

Based on Table 1, which refers to the maturity levels defined by ISO 37153:2017 and ISO 37107:2019, and Table 1, which shows the values of these levels, London (represented here by the real city) is characterized as having a maturity level of 4. Therefore, the city is considered intelligent, with actions that meet the current needs within the concept of smartness. The other cities were used only to mark the smart index of the real city, which, in this case, is represented by London. Thus, the utopian city has a maturity level of 5, the limit city has a maturity level of 2, and the reference city has a maturity level of 4. Figure 3 presents a graph with the cities analyzed.

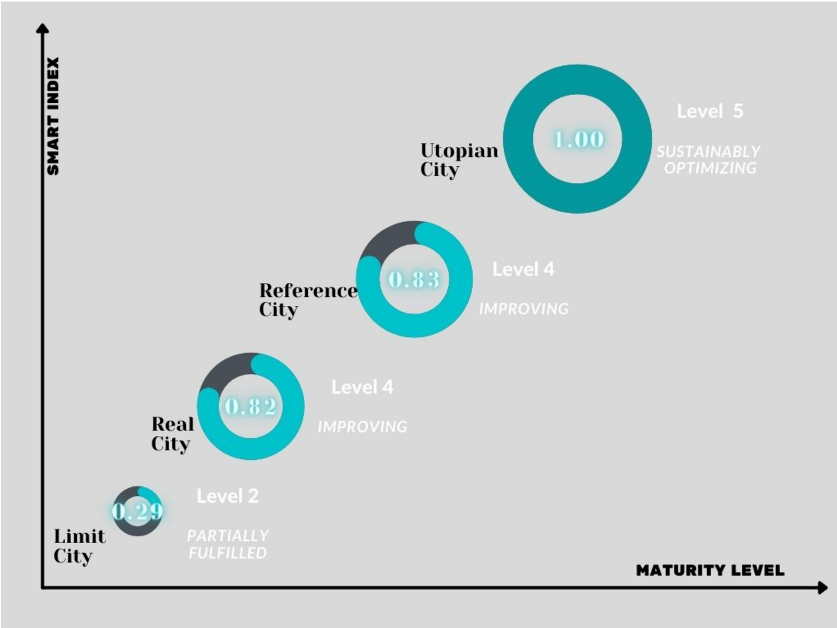

Figure 3. Maturity level.

In addition, for the MMSC to be considered predescriptive in addition to measuring the level of maturity of the real city, it must still be able to drive improvements so that the indicators can increase its performance value. Thus, the present methodology presents as a gap the impracticality of the prescriptive part of the model, as there is a complexity inserted in being able to distinguish, from each axis,the dimensions and indicators that negatively impact the maturity of the smart city.

5. Conclusions

Currently, it is the ISO norms that deal with the city of the future, referring to sustainability as an "umbrella" that includes both the intelligence and the resilience of cities. It was in this sense that ISOs 37120:2018, 37122:2019, and 37123:2019 were developed so that they can structure indicators capable of measuring the performance of a city with a focus on improving municipal services and the quality of life in its environment.

ISO 37122:2019 proposes an extremely technological focus for world cities, which is very distant for developing countries such as Brazil, that has a lot to evolve in terms of urban intelligence and sustainability. Thus, this study was based on ISO 37120:2018 because it brings the indicators that are already measurable by large organizations around the world, making the application of the proposed model based on reliable data.

In this work, a modified TOPSIS method was used, and, unlike its original function that ranks the alternatives, here it was used to generate a synthetic indicator called the smart index. Another modification made to the method was concerning the alternatives, since the alternatives utopian city, reference city, and limit city were fixed to guide the level of smart maturity of a city. One of the disadvantages of the TOPSIS method is the reverse ranking, which does not occur with the proposed method change in this study. In this way, in a future application, the beacon cities remain and only the real city is modified. Finally, the last modification concerns the positive ideal and negative ideal values which, unlike the traditional method, are fixed at 1 and 0 here, allowing the model to analyze the city based on the best and worst possible scenario, even if this scenario is not present in the fixed alternatives (utopian, reference, and limit).

The proposed model proved to be efficient for assessing the smart maturity level of a city. Despite indicating the smart level of the analyzed city, the model does not allow each indicator to be assessed separately, making it difficult to identify the improved points in the city under analysis.

In addition, it is important to note that the proposed model can be easily adapted to measure the city's maturity level for other ISOs, especially encompassing ISOs 37122:2019 and 37123:2019, which were not used in the study due to lack of reliable data regarding the indicators.

Despite its significant importance, for the model to be able to measure the maturity of the city, it is necessary to insert the largest number of indicators data, and these data need to be reliable. Many cities, despite calling themselves smart, do not disclose data related to indicators, even though they have actions related to them. Therefore, to be able to accurately measure the maturity of cities, these data must be easily accessible to researchers and nongovernmental organizations so that they can be analyzed constantly by the community.

Finally, the proposed MMSC has a quantitative structure with the aid of a hybrid multicriteria technique and variables belonging to internationally known standards, a structure that has not yet been explored in the literature so far.

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