

Evaluation of the Smart Cities Listed in Smart City Index 2021 by Using Entropy Based Copras and Aras Methodology

Emel Gelmez^{*}, Eren Özceylan[†]

Abstract. Smart cities are included in the literature as a technology-based concept that has been on the agenda in recent years and whose framework is constantly changing with the changes in technology. There are different frameworks and indexes to define the smartness of a city. Smart City Index 2021 published by Institute for Management Development (IMD) and Singapore University of Technology and Design (SUTD) is one of the accepted studies in the world. In the report of Smart City Index 2021, 118 cities are evaluated in five criteria namely health & safety, mobility, activities, opportunities (work & school) and governance. To re-evaluate the cities and compare the results, a Multi-Criteria Decision Making (MCDM) process including Entropy based Complex Proportional Assessment (COPRAS) and Additive Ratio Assessment (ARAS) methodology is applied in this paper. To prioritize the criteria, entropy weight method is used. 118 cities are ranked both technologically and structurally using the COPRAS and ARAS method. As a result of the analyses, according to these methods, the rankings of the smart cities are the same. Also, when technologically smart cities are listed, it is determined that the first three countries are Zhuhai, Shenzhen, Nanjing, and at the same time, Abu Dhabi, Chongqing, Hangzhou in terms of structurally.

Keywords: Smart City, Multi-Criteria Decision Making, Entropy, COPRAS, ARAS, Smart City Index 2021.

1. Introduction

In recent years, the concept of ‘smart city’ has been the subject of various studies and has become popular in international politics [1]. Smart cities have become a global phenomenon

^{*} Department of Business Administration, Selçuk University, 42130 Konya, Turkey, emelgelmez@selcuk.edu.tr, Orcid ID: 0000-0002-8774-607X

[†] Department of Industrial Engineering, Gaziantep University, 27100 Gaziantep, Turkey, erenozceylan@gmail.com, Orcid ID: 0000-0002-5213-6335

of the 21st century and are seen as a solution to the current challenges of urbanization [2]. Smart cities are cities that integrate information and communication technologies that aim to increase people's welfare levels [3]. In short, 'smart city' is the real 'smart planet' approach applied to a specific region, providing access to information and integrated management of cities [4].

Smart city is an emerging strategy that aims to improve the quality of life of citizens by using the most innovative technologies to support the specific needs of each city [5]. A smart city can be defined as a sustainable and efficient city center that provides high quality of life by using its resources optimally [6]. In addition, smart cities are defined by IBM as the use of information and communication technology [4] to detect, analyze and integrate the basic information of core systems in running cities. Most generally, smart city is understood as a region with a well-developed economy, modern infrastructure, high living standards and a favorable environment [7]. In this context, smart cities [8]:

- enable the collection and analysis of real-world urban data using software systems, server infrastructure, network infrastructure and client devices,
- provide solutions with instrumentation support and interconnection of sensors, actuators and mobile devices,
- can combine service production with an intelligent environment and use accessible information in its activities and decision-making processes. They also embrace the flow of information between the municipality and the urban or business community.

The application of Information and Communication Technology (ICT) in the context of the cities of the future is often expressed with the concept of smart city. Compared to the concept of digital city or intelligent city, the main focus is not limited to the role of ICT infrastructure. Rather, the main focus of the digital city is human capital/education, social and relational capital and environmental issues. In fact, these issues are considered to be some important drivers of urban growth [9]. In this context, the role and importance of smart cities is increasing day by day with the effect of digital transformation on a global scale. That is why it is of great importance to examine the subject. Within the scope of this study, the Smart City Index 2021 (SCI, 2021) report [10] has been used to examine smart cities. When this report is examined in detail, it is seen that it is suitable for the structure of MCDM problems.

MCDM is one of the fastest growing subjects of operations research [11] and finds a significant area of use. Especially the development of new methods and the improvement of old methods have significantly increased its role in different application areas [12]. It is one of the most important activities in areas such as decision making, business, service, manufacturing and product selection. Different qualities play an important role in choosing the best among the available alternatives. One of the important issues in the selection process is to find suitable standardized weight vectors [13], which are useful for bringing together the preferences of different decision makers. The decision-making process often considers more than one criterion at the same time. Also, multiple standard technologies are required to aid decision making. In MCDM conditions, decision makers should follow the rationality principle when choosing the most suitable alternative [14].

Each alternative in the MCDM problem can be defined by a set of criteria. The criteria can be qualitative and quantitative. It usually has different units of measurement and a different direction of optimization [15]. In order to find the best quantitative solution among the alternatives, the MCDM process provides the sequential solution of the alternatives to select the best alternatives [16]. In this context, the main aim of this study is to evaluate the

smart cities in the SCI (2021) published by the Institute for Management Development (IMD) and Singapore University of Technology and Design (SUTD) both technologically and structurally by using Entropy, COPRAS and ARAS methods from MCDM methods. Within the framework of this aim, the main research questions are as follows:

- Is there a difference in the ranking of smart cities structurally and technologically?
- Is there a difference in the ranking of smart cities in terms of the methods used, structurally and technologically?

When COPRAS and ARAS methods are evaluated separately, they bring various advantages if applied in solving a problem. As will be explained in more detail in the methodology section, both methods are advantageous in terms of ease of use [17, 18]. In addition, the superiority of the COPRAS method over MCDM methods is that it shows the utility of the alternatives [18]. However, no previous study has been found on the use of Entropy, COPRAS and ARAS methods together for technological and structural ranking of smart cities in the literature review. Therefore, the data obtained from the techniques used in this study will contribute to the literature. At this point, the importance of this study in terms of the relevant literature can be expressed as follows:

- It will enable the determination of the structural or technological status of the cities and, if necessary, to make improvements on the relevant issues.
- In the current report (SCI, 2021), it is important to make smart city rankings at two levels (technological and structural), since the general rankings of cities are given and the criteria are examined structurally and technologically in two groups.
- As the results obtained are an indicator of the structural and technological status of the smart cities, they can be considered as an important resource.

In line with the explanations above, the studies on the ranking of smart cities using MCDM methods have been examined initially in the second section. Then, various studies on the solution of different problems in the literature related to Entropy Based COPRAS and ARAS methodology have been examined. In the third section of the study, some information has been given about the SCI (2021) report. Based on the explanations, the process steps of Entropy COPRAS and ARAS methods have been explained within the scope of the research methodology in the fourth section. In the fifth section, the results of the analysis are given. And in the last section, comparisons have been made and the results have been examined and suggestions have been presented for future studies.

2. Literature Review on Smart City, Entropy Based COPRAS and ARAS Methodology

When the literature is examined, it is seen that MCDM methods are used in ordering smart cities and there are various studies on Entropy, COPRAS and ARAS methods on various subjects. Some of these studies can be summarized as in Table 1.

Table 1. Literature review

Some Studies on Smart Cities Using MCDM Methods		
Year	Author (s)	Application Area
2017	Stanković et al. [19]	The aim of this study is to provide a ranking of Central and Eastern European cities based on various elements of the smart performance of cities. In the study, the AHP (Analytic Hierarchy Process) method has been used to weight the criteria, and the Technique for Order Performance by Similarity to Ideal Solution (TOPSIS) method has been used to rank the alternatives. According to the results obtained, the general life satisfaction perceptions of citizens in European cities are not affected by the smart performance of the cities.
2017	Anand et al. [6]	Within the scope of this study, the importance of various criteria for sustainability in a smart city has been determined by using the fuzzy and fuzzy-AHP method. Sustainability indicators have been determined for smart city design in a developing country. The DEA:AR-CCR model has been adopted to determine the relative efficiency of each of the sustainability indicators for a smart city in the context of input and output criteria.
2018	Shen et al. [20]	In this study, a holistic evaluation of smart city performance has been made in the context of China. Within the scope of the study, Entropy and TOPSIS methods have been used. The study highlights that the overall smart city performance in China is at a relatively low level.
2019	Zhu et al. [21]	In the study conducted, the AHP and TOPSIS methods have been utilized to evaluate the resilience of 187 smart cities in China and rank them. It is seen within the scope of the study that the overall resilience of the smart cities is at a relatively low level.
2020	Sojda [22]	Within the scope of this study, the hierarchical structure of areas and indicators used in smart city evaluation is combined with the concept of multidimensional evaluation of facilities using the TOPSIS method.
2020	Nasution et al. [23]	In this study, a city suggestion suitable for the smart city structure has been made on the island of Sumatera. The TOPSIS method has been used within the scope of the research. According to the results of the analysis, it has been concluded that the city of Medan has the highest value in terms of being a smart city.
2020	Ozkaya and Erdin [24]	In this study, 44 cities in the Global Power City Index (GPCI) Year-book have been compared by Analytic Network Process (ANP) and TOPSIS method. According to the analysis, Tokyo,

		London, New York, Boston and Singapore are the top five cities in the overall smart city ranking, while Mumbai, Jakarta, Sao Paulo, Johannesburg and Cairo are at the end of the list.
Some Studies on Smart Cities Using MCDM Methods		
Year	Author (s)	Application Area
2020	Ogrodnik [25]	In this study, the largest Polish cities have been analyzed in terms of smart city indicators. The PROMETHEE method has been used in the study and the results have been examined.
2021	Sotirelis et al. [26]	In this study, PROMETHEE II method has been used to rank 17 cities worldwide. Singapore and Copenhagen are of the top performing cities.
2021	Koca et al. [27]	In this study, a hybrid methodology consisting of two stages has been developed and the concept of smart city has been examined. Firstly, a qualitative analysis has been conducted to determine the concept of smart city. Secondly, Decision Making Trial and Evaluation Laboratory (DEMATEL) technique has been used to examine the smart city by focusing on the dimensions derived from the literature in the form of six main and 33 sub-dimensions.
2021	Hajduk and Jelonek [28]	In this study, smart cities are listed in the context of energy based on MCDM method using ISO 37120 indicators. While the Entropy method has been used to weight the criteria, the TOPSIS method has been used to rank the alternatives. According to the results of the analysis, Porto is ranked as the first, while Buenos Aires is ranked as the last.
2021	Hajduk [29]	In this study, MCDM method has been used to rank smart cities. The TOPSIS technique has been used within the scope of the evaluation. As a result of the analysis, it has been determined that the city of Krakow has the highest value for being a smart city.
2022	Ye et al. [30]	Within the scope of the study, nine smart cities (Guangzhou, Shenzhen, Foshan, Dongguan, Zhaoqing, Jiangmen, Zhongshan, Huizhou, and Zhuhai) in the Pearl River Delta region (China) have been compared and ranked with the help of Weighted Sum Method (WSM), TOPSIS and Vise Kriterijumsa Optimizacija I Kompromisno Resenje (VIKOR), which are some MCDM methods. Entropy method has been used as the weighting method.
Some Studies on Various Subjects Using Entropy, COPRAS and ARAS Methods		
Year	Author (s)	Application Area
2012	Popovic et al. [31]	In this study, the selection of investment projects based on financial analysis criteria and the use of imprecise data have been discussed. In the model suggested within the scope of the study, the performances of alternative projects are expressed by using exact and interval values, and the best of the existing

		projects was selected by using the COPRAS and COPRAS-G methods.
2015	Makhesana [32]	In this study, COPRAS method has been used in rapid prototyping process.
Some Studies on Various Subjects Using Entropy, COPRAS and ARAS Methods		
Year	Author (s)	Application Area
2016	Adalı and Işık [33]	In this study, COPRAS and ARAS methods have been used to find a solution to the air conditioner selection problem. The AHP method has been used to weight the criteria. Air conditioning alternatives have been listed and the results have been compared by using the COPRAS and ARAS method.
2016	Săraru [34]	In this study, TOPSIS, ARAS and COPRAS methods have been used to select the optimum artificial lift method for a well from Romanian oil fields.
2016	Karabasevic et al. [35]	Within the scope of the study, corporate social responsibility indicators have been determined and companies were listed. Stepwise Weight Assessment Ratio Analysis (SWARA) and ARAS methods have been used.
2018	Singaravel et al. [36]	In this study, the ARAS method has been used to determine the optimum process parameters and a suitable coated tool in the turning process of AISI 4340 steel. The process parameters considered are cutting speed, feed rate, depth of cut and coated tools. This suggested method is suitable for solving the multi-criteria optimization of process parameters.
2021	Goswami and Behera [37]	Within the scope of this study, COPRAS and ARAS methods have been used to solve the problems of Material Handling Equipment selection. Entropy method has been used to weight the criteria.
2021	Lalić et al. [38]	Within the scope of the study, the efficiency of Serbian trade has been examined according to the COPRAS method. It has been concluded that the commercial efficiency in Serbia is the best in 2020.
2021	Gök-Kısa et al. [39]	In this study, the performance of five privatized ports (Mersin, Samsun, Bandırma, İskenderun, Derince) in Turkey has been evaluated with the MCDM approach. Entropy method has been used to weight the criteria. In ordering the alternatives, the results have been evaluated by using TOPSIS and ARAS methods.
2021	Nweze and Achebo [40]	In this study, the COPRAS-ARAS method has been applied to determine the optimum process parameters for the improvement of the mechanical properties of the weldment.

2021	Gorgulu et al. [41]	Within the scope of the study, UI GreenMetric 56 different Turkish Universities in Turkey in 2020 have been ranked according to their sustainability performance using the COPRAS method, considering 6 criteria. Entropy method has been used to weight the criteria. At the same time, universities have also been ranked by using the TOPSIS approach to observe how the ranking changes according to different scenarios.
Some Studies on Various Subjects Using Entropy, COPRAS and ARAS Methods		
Year	Author (s)	Application Area
2022	Karadağ Ak et al. [42]	In this study, the performance of development and investment banks operating in Turkey has been examined. The entropy method has been used to weight the criteria, and the ARAS method has been used to rank the alternatives.

Source: Created by the authors based on the relevant literature.

3. Smart City Index 2021

The data used in the analysis section of the study have been taken from the SCI (2021) report published by the Institute for Management Development (IMD) and Singapore University of Technology and Design (SUTD). Therefore, it is important to give information about this [10].

The IMD-SUTD Smart City Index evaluates the perceptions of the residents about the topics related to structures and technology applications offered to them in their cities. In this respect, 120 residents have been determined taking into account the SCI (2021), and rankings have been made in terms of the dimensions of structures, which refers to the existing infrastructure of 118 cities, and technology, which defines the technological products and services offered to the residents. Five main criteria as health & safety, mobility, activities, opportunities (work & school) and governance have been determined within the scope of the index. Also, the cities have been divided into four groups according to UN Human Development Index (HDI) scope of the economy which they are part of. Cities are assigned to a 'rating scale' (AAA to D) based on the perception-score of a given city compared to the scores of all other cities within the same group, within each HDI group. In this framework, the 118 cities have been subjected to general ranking and at the same time these five criteria have been evaluated both technologically and structurally.

Since it has been tried to make a decision depending on the five main criteria, when structure of the report is considered, it is seen that the rankings of the smart cities can be made through the MCDM methods. Accordingly, the rankings have been made by using the data included in the respective report (SCI, 2021) by means of the MCDM methods (Entropy based COPRAS and ARAS) for the purpose of determining the cities standing out both technologically and structurally in the ranking of the smart cities in this study.

4. Methodology

In this section of the study, some information is given about the methods to be used in the research. The Entropy method used in weighting the criteria and the COPRAS and ARAS method used in ranking the alternatives can be explained as follows:

4.1. Entropy Method

MCDM refers to decision making in the presence of multiple criteria that are often in conflict with each other. A typical MCDM problem includes a set of alternatives to be evaluated and a set of criteria for evaluating alternatives [43]. In other words, MCDM is a discipline that allows the evaluation of different and conflicting attributes to prioritize or select various alternatives to assist the decision maker. The framework of the MCDM generally includes four elements. These are listed as follows [44]:

- Criterias,
- Alternatives,
- Weight of attribute,
- Performance ratings of options for criteria.

MCDM methods have been applied to different subjects and there is the best solution for choosing the best alternative [45]. An important issue in MCDM analysis is the determination of individual criterion weights. Weights are a measure of the relative importance of a criterion relative to alternatives in multi-criteria problems and usually take numerical values between 0 and 1 [46]. In this context, the concept of Entropy [47], originally derived from thermodynamics, is first introduced to the literature by Rudolph Clausius (1865) as a measure of disorder and uncertainty in a system [48].

One of the most difficult issues in MCDM problems is assigning an accurate weight to the criteria by which the alternatives will be ranked. Entropy is a method used to assign weights to criteria [49]. In other words, the Entropy method is used to determine the objective weights of the criteria depending on the data in the decision matrix [50]. In this respect, the technique is an objective weighting method by its nature [51]. Therefore, the weights calculated by this method are also known as objective weights. It consists of the normalization of decision matrix with Equation (1), calculating the Entropy value with Equation (2), and calculating the weight vector with Equation (3) [52].

Step 1. Normalized values of the decision-making matrix are calculated by Equation (1).

$$R_{ij} = \frac{X_{ij}}{\sum_{i=1}^m X_{ij}} \quad (1)$$

$\sum X_{ij}$ value is calculated by summing all values of a criterion of all alternatives.

Step 2. Entropy value is calculated by Equation (2).

$$e_j = -h \sum_{i=1}^m R_{ij} \ln R_{ij}, j = 1, 2, \dots, n \quad (2)$$

Within the scope of the e_j entropy value; $h = \frac{1}{\ln(m)}$ is calculated, with m standing for a series of alternatives.

Step 3. Weights are calculated by Equation (3).

$$w_j = \frac{1-e_j}{\sum_{j=1}^n (1-e_j)} j=1, 2, \dots, n \quad (3)$$

w_j stands for weight of criteria, with $1 - e_j = d_j$ being the degree of diversification.

4.2. COPRAS (Complex Proportional Assessment) Method

The COPRAS (Complex Proportional Assessment) method [53], which was included in the literature in 1996, is a method that evaluates the superiority of one alternative to another and makes it possible to compare alternatives [54]. The COPRAS method assumes that the ranking of alternatives, the significance and priority of the alternatives under investigation are directly and proportionally dependent on a criterion system [31]. In other words, it is a ranking based on the relative importance (weight) of each alternative. By using COPRAS method, the best alternative (solution) is determined, taking into account the positive and negative sides for the ideal solution [55]. COPRAS considers the performance of alternatives according to different criteria and corresponding weights, using a gradual ranking and evaluation procedure in pursuant of the significance and utility degree of alternatives to make the best decision [56]. The advantages of the COPRAS method can be listed as follows [18]:

- Compared to other MCDM methods such as AHP and TOPSIS, it is a very simple method that requires less calculation time.
- It is possible to list the alternatives or options.
- The method provides the opportunity to evaluate both qualitative and quantitative criteria.
- COPRAS is capable of calculating both maximizing and minimizing criteria. In the evaluation process, both criteria are evaluated separately. Some MCDM methods, such as Simple Additive Weighting (SAW) for instance, require conversion to evaluate negative values, and this process takes a long time for the decision maker and creates a complex situation.
- The superiority of COPRAS over other MCDM methods is that it shows the utility of the alternatives. It also shows how good or how bad the alternatives are compared to each other, as a percentage.

The progress steps of the COPRAS method are as [57, 58]:

Step 1. Decision matrix ($F = [f_{ij}]_{n \times m}$) is normalised using Equation (4).

The normalized decision matrix is denoted by $G = [g_{ij}]_{n \times m}$. The purpose of normalization is to obtain different dimensionless values to compare all criteria.

$$g_{ij} = \frac{f_{ij}}{\sum_{j=1}^m f_{ij}} \quad i = 1, 2, \dots, n; j = 1, 2, \dots, m \quad (4)$$

Step 2. The weighted normalized decision matrix $Y = [y_{ij}]_{n \times m}$ is determined using Equation (5).

$$y_{ij} = w_i f_{ij} \quad i = 1, 2, \dots, n; j = 1, 2, \dots, m \quad (5)$$

where g_{ij} , is the normalized value of j_{th} alternative according to i_{th} criterion.

Step 3. The sums of the weighted normalized values are calculated for both the beneficial and non-beneficial criteria. These sums are calculated using Equation (6) and Equation (7).

$$K_{+j} = \sum_{i=1}^n y_{+ij} \quad (6)$$

$$K_{-j} = \sum_{i=1}^n y_{-ij} \quad (7)$$

where y_{+ij} and y_{-ij} are the weighted normalised values of the beneficial and non-beneficial criteria, respectively.

Step 4. The significance of the alternatives is determined by defining the characteristics of the positive alternatives K_{+j} and negative alternatives K_{-j} .

Step 5. The relative significance or priorities of the alternatives are determined. The priorities of the candidate alternatives are calculated based on C_j . The relative significance value of the j_{th} alternative, C_j , is calculated by using Equation (8).

$$C_j = K_{+j} + \frac{K_{-min} \sum_{j=1}^m K_{-j}}{K_{-j} \sum_{j=1}^m (K_{-min}/K_{-j})} \quad (j = 1, 2, \dots, m) \quad (8)$$

where K_{-min} is the minimum value of K_{-j} .

Step 6. The quantitative utility (U_j) is calculated for the j_{th} alternative. The utility level of an alternative is causally related to its relative significance value (C_j). The degree of utility of an alternative, determining the rank of the alternative, is determined by comparing the priorities of all alternatives for efficiency. It is calculated using Equation (9).

$$U_j = \left[\frac{C_j}{C_{max}} \right] \times 100 \quad (9)$$

4.3. ARAS (Additive Ratio Assessment) Method

The ARAS method is presented to the literature by Zavadskas and Turskis (2010) [15]. This method aims to handle situations where evaluation information has different units of measurement [59]. Although the ARAS method is a newly proposed method, it is an effective and easy-to-use [11]. MCDM method that uses the concept of utility theory and quantitative measurements to determine the best alternative among the given alternatives [60]. In the ARAS method, the concept of optimality degree is used to rank the alternatives [61]. In the method, the scores of the utility functions of the alternatives that are the subject of the research are compared with the score of the utility function of the optimal alternative [62]. The advantages of the ARAS method can be listed as follows [17]:

- Direct and proportional relationship with criterion weights,
- Ability to solve extremely complex problems,
- Ease of use for the application,
- Effectiveness,
- Ease of the extension in different fuzzy environments.

The ARAS method consists of four steps and the progress steps are as follows [15]:

Step 1. The decision matrix is created. In the decision matrix, there is a separate line added by the researcher and containing the optimal values for each criterion. Depending on whether the criterion shows maximum or minimum characteristics, the optimal value is calculated with the help of Equation (10) and Equation (11).

In case of maximization;

$$x_{0j} = \max_i x_{ij} \quad (10)$$

In case of minimization;

$$x_{0j} = \min_i x_{ij} \quad (11)$$

Step 2. Normalized decision matrix is created. In the ARAS method, $\bar{X}$ normalized decision matrix consists of $\bar{x}_{ij}$ values. The $\bar{x}_{ij}$ are calculated depending on whether the criterion shows the maximum or minimum feature. If maximum criterion values are considered better, normalized values are calculated with the help of Equation (12).

$$\bar{x}_{ij} = \frac{x_{ij}}{\sum_{i=0}^m x_{ij}} \quad (12)$$

If the criterion performance values are considered better to be minimum, the normalization process is performed with Equation (13) and Equation (14).

$$x_{ij}^* = \frac{1}{x_{ij}}; \quad (13)$$

$$\bar{x}_{ij} = \frac{x_{ij}^*}{\sum_{i=0}^m x_{ij}^*} \quad (14)$$

Step 3. A weighted normalized decision matrix is created. After the normalized decision matrix is formed, w_j weighted normalized decision matrix is calculated with the help of the calculated $\bar{X}$ weights. The weight values of the criteria meet the condition $0 < w_j < 1$ and the sum of the weights is as shown in Equation (15).

$$\sum_{j=1}^n w_j = 1 \quad (15)$$

The weighted normalized values of $\hat{x}_{ij}$ are obtained with the help of Equation (16).

$$\hat{x}_{ij} = \bar{x}_{ij} \cdot w_{ij} \quad (16)$$

Step 4. Optimal values are calculated. Lastly, the optimal values for each alternative are calculated by Equation (17).

$$S_i = \sum_{j=1}^n \hat{x}_{ij}, i = 0, I, \dots, m \quad (17)$$

S_i is the value of optimality function of i alternative. By proportioning the S_i values of the alternatives to the optimal value of S_o the utility degrees of K_i are calculated with the help of Equation (18).

$$K_i = \frac{S_i}{S_o}, i = 0, I, \dots, m \quad (18)$$

The utility function values of the alternatives can be calculated by using the K_i ratios that take values in the range of $[0,1]$. Alternatives are evaluated by arranging the values from the largest to the smallest.

5. Evaluation of the Findings of the Research

In this section of the study, the process steps of the Entropy used to weight the criteria and the COPRAS and ARAS methods used to rank the alternatives are mentioned. The process steps can be explained as follows.

5.1. Prioritization of the Criteria by Using the Entropy Weight Method

Within the scope of the study, considering the SCI (2021) published by the Institute for Management Development (IMD) and Singapore University of Technology and Design (SUTD), 118 cities have been ranked by COPRAS and ARAS method in terms of structure and technology. Five criteria in the SCI (2021), namely health & safety, mobility, activities, opportunities (work & school) and governance have been taken into account in ranking the cities. The weights of the criteria to be used in the ranking of smart cities have been calculated by the Entropy method. As a result of the values obtained, smart cities are ranked technologically and structurally according to the COPRAS and ARAS methods. An important issue here is that no modifications were made in the solution of the problem, which was created by using the COPRAS and ARAS methods. The five criteria and codes used in the evaluation of cities are presented in Table 1.

Table 1. Criteria and codes used in the evaluation

Code	Criteria
C1	Health & Safety
C2	Mobility
C3	Activities
C4	Opportunities (Work & School)
C5	Governance

In order to rank the cities, the values of the five basic criteria in the SCI (2021) report have been calculated by using the arithmetic average, both technologically and structurally. The Decision Matrix created in this context is in Table A1, and its details are given in Appendix.

In determining the criterion weights, the steps of the Entropy method have been calculated in order, the entropy value for each criterion is e_j . And also, the uncertainty d_j as the degree of diversification and the weight value w_j for each criterion have been calculated and the weights have been determined. Table 2 below shows the values of e_j , d_j and w_j .

Table 2. e_j , d_j and w_j values

	Technologies					Structures				
	C1	C2	C3	C4	C5	C1	C2	C3	C4	C5
e_j	0.9965	0.9963	0.9993	0.9976	0.9952	0.0444	0.0447	0.0443	0.0443	0.0444
d_j	0.0035	0.0037	0.0007	0.0024	0.0048	0.9556	0.9553	0.9557	0.9557	0.9556
w_j	0.2305	0.2470	0.0478	0.1601	0.3145	0.2000	0.1999	0.2000	0.2000	0.2000
Rank	3	2	5	4	1	3	5	2	1	4

When Table 2 is examined, it is seen that the most important criteria differ in terms of technology and structure according to the results of the Entropy method. While the most

important criterion in terms of technology is governance (C5), it has been determined as opportunities (work & school) (C4) in terms of structure. These weight criteria have been used to rank the cities and in the COPRAS and ARAS methods.

5.2. Ranking the Cities by Using COPRAS and ARAS Methods

Rankings have been created by using the COPRAS and ARAS methods based on the criterion weights obtained from the Entropy method in ordering the cities. Cities are listed both technologically (Table 3) and structurally (Table 4), and the results are given in Table 3 and Table 4 below.

Table 3. Technological rankings of the smart cities by using COPRAS and ARAS methods

COPRAS			ARAS		
Cities	U_j	Rn	Cities	K_j	Rn
Zhuhai	1.0000	1	Zhuhai	0.9993	1
Shenzhen	0.9620	2	Shenzhen	0.9614	2
Nanjing	0.9556	3	Nanjing	0.9549	3
Guangzhou	0.9507	4	Guangzhou	0.9501	4
Hangzhou	0.9412	5	Hangzhou	0.9405	5
Beijing	0.9341	6	Beijing	0.9335	6
Shanghai	0.9299	7	Shanghai	0.9293	7
Chongqing	0.9167	8	Chongqing	0.9161	8
Tianjin	0.9104	9	Tianjin	0.9098	9
Chengdu	0.8873	10	Chengdu	0.8867	10
Abu Dhabi	0.8609	11	Abu Dhabi	0.8603	11
Dubai	0.8325	12	Dubai	0.8319	12
Hanoi	0.8221	13	Hanoi	0.8215	13
Taipei City	0.8093	14	Taipei City	0.8088	14
Riyadh	0.8072	15	Riyadh	0.8067	15
Ho Chi Minh City	0.8072	16	Ho Chi Minh City	0.8067	16
New Delhi	0.8068	17	New Delhi	0.8063	17
Mumbai	0.8049	18	Mumbai	0.8043	18
Jakarta	0.7994	19	Jakarta	0.7989	19
Singapore	0.7793	20	Singapore	0.7788	20
Bengaluru	0.7624	21	Bengaluru	0.7619	21
Hyderabad	0.7526	22	Hyderabad	0.7521	22
Bangkok	0.7501	23	Bangkok	0.7496	23
Moscow	0.7406	24	Moscow	0.7401	24
Seoul	0.7321	25	Seoul	0.7316	25
Medan	0.7259	26	Medan	0.7254	26
Medina	0.7176	27	Medina	0.7172	27
Ankara	0.7156	28	Ankara	0.7152	28
Istanbul	0.7098	29	Istanbul	0.7093	29
Manila	0.7082	30	Manila	0.7077	30
New York	0.7051	31	New York	0.7047	31
Makassar	0.6991	32	Makassar	0.6986	32
Los Angeles	0.6948	33	Los Angeles	0.6944	33
Kuala Lumpur	0.6911	34	Kuala Lumpur	0.6907	34
Madrid	0.6881	35	Madrid	0.6877	35
Warsaw	0.6843	36	Warsaw	0.6839	36
St, Petersburg	0.6796	37	St, Petersburg	0.6791	37
Hong Kong	0.6669	38	Hong Kong	0.6665	38
Medellin	0.6646	39	Medellin	0.6642	39
Kiev	0.6631	40	Kiev	0.6627	40
Busan	0.6622	41	Busan	0.6618	41

Bilbao	0.6618	42	Bilbao	0.6613	42
London	0.6570	43	London	0.6565	43
Tallinn	0.6567	44	Tallinn	0.6562	44
Auckland	0.6489	45	Auckland	0.6485	45
Helsinki	0.6460	46	Helsinki	0.6456	46
Zurich	0.6457	47	Zurich	0.6453	47
Tel Aviv	0.6447	48	Tel Aviv	0.6443	48
Cairo	0.6432	49	Cairo	0.6427	49
Oslo	0.6400	50	Oslo	0.6396	50
Sydney	0.6398	51	Sydney	0.6394	51
Krakow	0.6374	52	Krakow	0.6370	52
Amsterdam	0.6359	53	Amsterdam	0.6354	53
COPRAS			ARAS		
Cities	U_j	Rn	Cities	K_j	Rn
Washington D,C	0.6358	54	Washington D,C	0.6354	54
Bordeaux	0.6346	55	Bordeaux	0.6342	55
Copenhagen	0.6345	56	Copenhagen	0.6341	56
Melbourne	0.6345	57	Melbourne	0.6341	57
Lille	0.6317	58	Lille	0.6313	58
Bologna	0.6302	59	Bologna	0.6298	59
Lyon	0.6296	60	Lyon	0.6292	60
Leeds	0.6291	61	Leeds	0.6287	61
Lausanne	0.6290	62	Lausanne	0.6286	62
Prague	0.6280	63	Prague	0.6275	63
Milan	0.6269	64	Milan	0.6265	64
Geneva	0.6244	65	Geneva	0.6240	65
Paris	0.6223	66	Paris	0.6219	66
Lisbon	0.6222	67	Lisbon	0.6218	67
Toronto	0.6208	68	Toronto	0.6203	68
Zaragoza	0.6205	69	Zaragoza	0.6201	69
Barcelona	0.6171	70	Barcelona	0.6167	70
Dusseldorf	0.6168	71	Dusseldorf	0.6164	71
Chicago	0.6096	72	Chicago	0.6092	72
Munich	0.6082	73	Munich	0.6078	73
Brisbane	0.6070	74	Brisbane	0.6066	74
Rotterdam	0.6061	75	Rotterdam	0.6057	75
Vienna	0.6026	76	Vienna	0.6022	76
Vancouver	0.5981	77	Vancouver	0.5978	77
Seattle	0.5973	78	Seattle	0.5970	78
Denver	0.5967	79	Denver	0.5963	79
The Hague	0.5966	80	The Hague	0.5962	80
Manchester	0.5964	81	Manchester	0.5960	81
Cape Town	0.5961	82	Cape Town	0.5958	82
Budapest	0.5957	83	Budapest	0.5953	83
San Francisco	0.5951	84	San Francisco	0.5947	84
Buenos Aires	0.5948	85	Buenos Aires	0.5944	85
Bratislava	0.5934	86	Bratislava	0.5931	86
Birmingham	0.5928	87	Birmingham	0.5924	87
Montreal	0.5896	88	Montreal	0.5892	88
Newcastle	0.5885	89	Newcastle	0.5881	89
Glasgow	0.5871	90	Glasgow	0.5868	90
Rabat	0.5823	91	Rabat	0.5819	91
Brussels	0.5799	92	Brussels	0.5796	92
Mexico City	0.5791	93	Mexico City	0.5787	93
Dublin	0.5787	94	Dublin	0.5783	94
Marseille	0.5783	95	Marseille	0.5779	95
Boston	0.5769	96	Boston	0.5765	96
Hamburg	0.5734	97	Hamburg	0.5731	97
Philadelphia	0.5692	98	Philadelphia	0.5688	98

Stockholm	0.5691	99	Stockholm	0.5688	99
Bucharest	0.5682	100	Bucharest	0.5679	100
Gothenburg	0.5647	101	Gothenburg	0.5644	101
Berlin	0.5622	102	Berlin	0.5619	102
Sofia	0.5472	103	Sofia	0.5468	103
Phoenix	0.5461	104	Phoenix	0.5457	104
Sao Paulo	0.5447	105	Sao Paulo	0.5444	105
Hanover	0.5437	106	Hanover	0.5433	106
Santiago	0.5420	107	Santiago	0.5416	107
Nairobi	0.5247	108	Nairobi	0.5243	108
Bogota	0.5223	109	Bogota	0.5220	109
Athens	0.5174	110	Athens	0.5171	110
COPRAS			ARAS		
Cities	U_j	Rn	Cities	K_j	Rn
Tokyo	0.5115	111	Tokyo	0.5112	111
Kiel	0.5097	112	Kiel	0.5094	112
Lagos	0.4910	113	Lagos	0.4907	113
Rome	0.4881	114	Rome	0.4878	114
Rio de Janeiro	0.4748	115	Rio de Janeiro	0.4745	115
San José	0.4689	116	San José	0.4686	116
Osaka	0.4499	117	Osaka	0.4496	117
Abuja	0.4478	118	Abuja	0.4475	118

When the SCI (2021) is examined, it is seen that the cities are not ranked technologically and structurally, but are subject to a general ranking for 2021. At the same time, in the SCI (2021) report, cities have technologically and structurally been assigned to groups according to the 'rating scale' (AAA to D), and it has been determined in which of these four groups the smart cities are located. When evaluated from this point of view, it is important to rank the cities according to structural and technological features.

When Table 3 is examined, it is seen that there is no difference in the technological order of the cities according to the COPRAS and ARAS methods. When examined in detail, it is seen that Zhuhai ranks first in terms of technology. When the SCI (2021) report is examined, it is seen that the scores of the sub-items of health & safety, mobility, activities, opportunities (work & school), governance dimensions are also high. Among these features, activities attract a lot of attention and its effectiveness in technology is seen. This situation supports the effectiveness of Zhuhai as a technology. Zhuhai is followed by Shenzhen, Nanjing, Guangzhou, Hangzhou, Beijing, Shanghai, Chongqing, Tianjin and Chengdu. According to both COPRAS and ARAS methods, Abuja is at the bottom of the list. When the SCI (2021) report is examined, it is seen that, unlike Zhuhai, Abuja has low scores on the sub-items of health & safety, mobility, activities, opportunities (work & school), and governance. Abuja is followed by Osaka (117), San José (116), Rio de Janeiro (115), Rome (114), Lagos (113), Kiel (112), Tokyo (111), Athens (110), Bogota (109), and Nairobi (108). In this case, it can be suggested that the technology structures of these cities are low and should be developed.

When the SCI (2021) report is examined in detail, it is seen that Bordeaux, Glasgow, Istanbul, Kiel, Lausanne, Leeds, Lille, Medina, San José are new on the list. In terms of these cities, Istanbul (29) ranks first in terms of technology, among the cities that are new on the list according to the COPRAS and ARAS methods. While Istanbul is followed by Berdaux (55), it is seen that San José (116) comes the last.

When the data obtained within the scope of the study are compared with the SCI (2021) report, it is seen that there are differences between the ranking of the cities in terms of technology and the general ranking of the report. It is considered that this situation may be

due to the ranking of separate cities by taking the SCI (2021) report as a reference in terms of technology and structure within the scope of the study.

Table 4. Structural rankings of the smart cities by using COPRAS and ARAS methods

COPRAS			ARAS		
Cities	U_j	Rn	Cities	K_j	Rn
Abu Dhabi	1.0000	1	Abu Dhabi	0.9319	1
Chongqing	0.9687	2	Chongqing	0.9028	2
Hangzhou	0.9633	3	Hangzhou	0.8978	3
Dubai	0.9615	4	Dubai	0.8961	4
Tianjin	0.9348	5	Tianjin	0.8712	5
Zhuhai	0.9320	6	Zhuhai	0.8686	6
Guangzhou	0.9154	7	Guangzhou	0.8531	7
Beijing	0.8997	8	Beijing	0.8385	8
Helsinki	0.8920	9	Helsinki	0.8313	9
Chengdu	0.8904	10	Chengdu	0.8298	10
Zurich	0.8894	11	Zurich	0.8288	11
Nanjing	0.8869	12	Nanjing	0.8266	12
Shenzhen	0.8832	13	Shenzhen	0.8231	13
Oslo	0.8792	14	Oslo	0.8194	14
Bilbao	0.8745	15	Bilbao	0.8150	15
Copenhagen	0.8712	16	Copenhagen	0.8119	16
Geneva	0.8607	17	Geneva	0.8021	17
Shanghai	0.8502	18	Shanghai	0.7924	18
Singapore	0.8201	19	Singapore	0.7643	19
Newcastle	0.8106	20	Newcastle	0.7555	20
Hanover	0.8090	21	Hanover	0.7540	21
Ho Chi Minh City	0.8087	22	Ho Chi Minh City	0.7537	22
Vienna	0.8005	23	Vienna	0.7461	23
The Hague	0.7992	24	The Hague	0.7448	24
Hanoi	0.7917	25	Hanoi	0.7378	25
Riyadh	0.7911	26	Riyadh	0.7372	26
Dusseldorf	0.7906	27	Dusseldorf	0.7368	27
Hyderabad	0.7878	28	Hyderabad	0.7342	28
Amsterdam	0.7866	29	Amsterdam	0.7331	29
Brisbane	0.7845	30	Brisbane	0.7311	30
Auckland	0.7841	31	Auckland	0.7307	31
Bologna	0.7825	32	Bologna	0.7292	32
Hamburg	0.7749	33	Hamburg	0.7222	33
Ankara	0.7637	34	Ankara	0.7118	34
Gothenburg	0.7548	35	Gothenburg	0.7034	35
Bengaluru	0.7546	36	Bengaluru	0.7032	36
Bordeaux	0.7424	37	Bordeaux	0.6919	37
Washington D.C	0.7393	38	Washington D.C	0.6890	38
Taipei City	0.7352	39	Taipei City	0.6852	39
Denver	0.7259	40	Denver	0.6765	40
Boston	0.7254	41	Boston	0.6761	41
Montreal	0.7243	42	Montreal	0.6750	42
Melbourne	0.7169	43	Melbourne	0.6681	43
Glasgow	0.7074	44	Glasgow	0.6593	44
Medellin	0.7064	45	Medellin	0.6584	45
Manchester	0.7059	46	Manchester	0.6579	46
New Delhi	0.7058	47	New Delhi	0.6578	47
Krakow	0.7029	48	Krakow	0.6550	48
Prague	0.6999	49	Prague	0.6523	49
Brussels	0.6995	50	Brussels	0.6519	50

Vancouver	0.6984	51	Vancouver	0.6509	51
Dublin	0.6970	52	Dublin	0.6495	52
Madrid	0.6961	53	Madrid	0.6487	53
COPRAS			ARAS		
Cities	U_j	Rn	Cities	K_j	Rn
Busan	0.6951	54	Busan	0.6478	54
Barcelona	0.6897	55	Barcelona	0.6427	55
Lausanne	0.6877	56	Lausanne	0.6409	56
Seattle	0.6867	57	Seattle	0.6399	57
Berlin	0.6858	58	Berlin	0.6391	58
Chicago	0.6839	59	Chicago	0.6374	59
Jakarta	0.6821	60	Jakarta	0.6357	60
Munich	0.6798	61	Munich	0.6336	61
Sydney	0.6714	62	Sydney	0.6257	62
Toronto	0.6688	63	Toronto	0.6233	63
Birmingham	0.6684	64	Birmingham	0.6229	64
New York	0.6682	65	New York	0.6227	65
Tallinn	0.6675	66	Tallinn	0.6221	66
Kiel	0.6675	67	Kiel	0.6221	67
Lille	0.6597	68	Lille	0.6148	68
Milan	0.6588	69	Milan	0.6139	69
Moscow	0.6543	70	Moscow	0.6098	70
Stockholm	0.6493	71	Stockholm	0.6051	71
Makassar	0.6487	72	Makassar	0.6046	72
Hong Kong	0.6472	73	Hong Kong	0.6031	73
Lyon	0.6433	74	Lyon	0.5995	74
Rotterdam	0.6414	75	Rotterdam	0.5977	75
Leeds	0.6401	76	Leeds	0.5966	76
Kuala Lumpur	0.6365	77	Kuala Lumpur	0.5932	77
Zaragoza	0.6341	78	Zaragoza	0.5910	78
Phoenix	0.6285	79	Phoenix	0.5857	79
Bangkok	0.6248	80	Bangkok	0.5823	80
Medan	0.6226	81	Medan	0.5803	81
Osaka	0.6199	82	Osaka	0.5777	82
St. Petersburg	0.6180	83	St. Petersburg	0.5759	83
Warsaw	0.6141	84	Warsaw	0.5723	84
Tel Aviv	0.6086	85	Tel Aviv	0.5672	85
Bratislava	0.6075	86	Bratislava	0.5662	86
Medina	0.6020	87	Medina	0.5611	87
Cape Town	0.5993	88	Cape Town	0.5585	88
Marseille	0.5964	89	Marseille	0.5558	89
San Francisco	0.5921	90	San Francisco	0.5518	90
Los Angeles	0.5893	91	Los Angeles	0.5492	91
Budapest	0.5867	92	Budapest	0.5468	92
Mumbai	0.5847	93	Mumbai	0.5449	93
Buenos Aires	0.5815	94	Buenos Aires	0.5419	94
London	0.5811	95	London	0.5415	95
Lisbon	0.5713	96	Lisbon	0.5324	96
Philadelphia	0.5692	97	Philadelphia	0.5305	97
Abuja	0.5559	98	Abuja	0.5181	98
Paris	0.5474	99	Paris	0.5102	99
Tokyo	0.5454	100	Tokyo	0.5083	100
Cairo	0.5404	101	Cairo	0.5036	101
Manila	0.5358	102	Manila	0.4993	102
Kiev	0.5233	103	Kiev	0.4877	103
San José	0.5186	104	San José	0.4833	104
Seoul	0.5148	105	Seoul	0.4798	105
Bucharest	0.4933	106	Bucharest	0.4597	106
Rabat	0.4912	107	Rabat	0.4578	107

Lagos	0.4876	108	Lagos	0.4545	108
Bogota	0.4693	109	Bogota	0.4373	109
Nairobi	0.4693	110	Nairobi	0.4373	110
COPRAS			ARAS		
Cities	U_j	Rn	Cities	K_j	Rn
Santiago	0.4592	111	Santiago	0.4280	111
Athens	0.4477	112	Athens	0.4172	112
Sofia	0.4390	113	Sofia	0.4091	113
Mexico City	0.4383	114	Mexico City	0.4085	114
Istanbul	0.3923	115	Istanbul	0.3656	115
Rome	0.3842	116	Rome	0.3580	116
Rio de Janeiro	0.3269	117	Rio de Janeiro	0.3047	117
Sao Paulo	0.3266	118	Sao Paulo	0.3043	118

When Table 4 is examined, it is seen that there is no difference in the ranking of the cities when it comes to structural features according to the COPRAS and ARAS methods. However, there is a difference between ranking cities according to their structural features and ranking them technologically. In this framework, firstly, the ranking of the cities according to their structural characteristics will be examined, and then it is considered that it will be beneficial to make comparisons according to both levels (technological-structural).

When Table 4 is examined, it is seen that Abu Dhabi ranks first in terms of structure. When this situation is compared with the SCI (2021) report, it is seen that Abu Dhabi's scores on the sub-items of health & safety, mobility, activities, opportunities (work & school), and governance are also high. However, it is seen that the item 'Finding housing with rent equal to 30% or less of a monthly salary is not a problem' has the lowest score in these dimensions. It can be stated that this is a situation that needs improvement. Among these features, activities attract a lot of attention and its effectiveness in structure is seen. The high average scores can also be expressed as an indicator of Abu Dhabi's structural effectiveness. Abu Dhabi is followed by Chongqing, Hangzhou, Dubai, Tianjin, Zhuhai, Guangzhou, Beijing, Helsinki, Chengdu.

When Table 4 is examined in the context of the cities in the last row of the list, it is seen that Sao Paulo is the last city according to the COPRAS and ARAS methods. When the SCI (2021) report is examined in detail, it is seen that unlike Abu Dhabi, Sao Paulo has low scores for the sub-items of health & safety, mobility, activities, opportunities (work & school), governance. According to the results of the analysis, Sao Paulo is followed by Rio de Janeiro (117), Rome (116), Istanbul (115), Mexico City (114), Sofia (113), Athens (112), Santiago (111), Nairobi (110), Bogota (109), and Lagos (108). In this case, it can be suggested that the structural features of these cities are low and should be developed.

Bordeaux, Glasgow, Istanbul, Kiel, Lausanne, Leeds, Lille, Medina and San José, which have just been included in the SCI (2021) index, appear to be new on the list. When these cities are examined as they are evaluated in terms of technology, it is seen that Bordeaux (37), one of the new cities in the list according to COPRAS and ARAS methods, is structurally in the first place. Glasgow (44) follows Bordeaux, while San José (104) is the last.

When ranked in terms of structural features according to COPRAS and ARAS methods, it is noteworthy that Bogota (109) is in the same order in both methods. In addition, a remarkable issue is that Istanbul (29), which is at the top of the ranking in terms of technological features and newly included in the SCI (2021) index, is at the bottom of the list when evaluated in terms of structural features. In addition, Bordeaux, which is one of the new

cities on the list, ranks first in terms of structure (37) and ranks second in terms of technology (55).

When the data obtained within the scope of the study are compared with the SCI (2021) report, it is seen that there are differences in the ranking of the cities from the general ranking of the report in terms of structure. It is considered that this situation may be due to the ranking of separate cities by taking the SCI (2021) report as a reference in terms of technology and structure within the scope of the study. When Table 3 and Table 4 are examined, it is seen that there are differences in the rankings of smart cities. In this context, the research question ‘Is there a difference in the structural and technological smart city rankings?’ can be answered as ‘yes, there is a difference’.

As stated in the application part, the rankings obtained from the ARAS and COPRAS methods are exactly the same. However, although both methods give the same results, structural and technological differences occur in the order of the cities. In this context, the research question determined as ‘structural and technological’ can be answered as ‘no, there is no difference’.

Based on the explanations, the technological and structural ranking of the cities according to the COPRAS and ARAS method is presented in Figure 1.

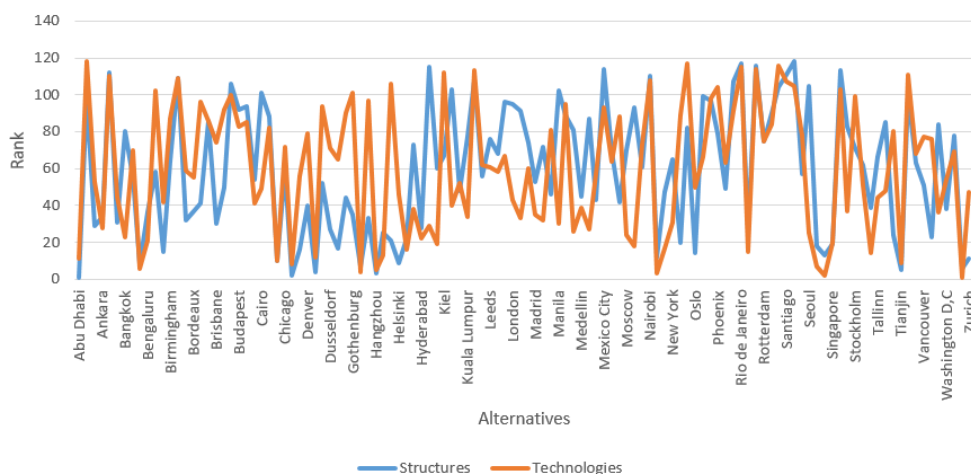


Figure 1. Technological and structural rankings of the smart cities by using COPRAS and ARAS methods

Based on the explanations above, as it can be seen in Figure 1, when Table 3 and Table 4 are examined, it is seen that there are differences in the rankings of the cities when ranked technologically and structurally. According to the results obtained, when the cities included in the list are ranked technologically, it is seen that Zhuhai, Shenzhen, Nanjing, Guangzhou, Hangzhou, Beijing, Shanghai, Chongqing, Tianjin, Chengdu are of the top cities on the list. Likewise, it has been determined that Rome (114), Rio de Janeiro (115), San José (116), Osaka (117) and Abuja (118) are at the end of the list.

When the cities are ranked in terms of structural characteristics, it is seen that Abu Dhabi, Chongqing, Hangzhou, Dubai, Tianjin, Zhuhai, Guangzhou, Beijing, Helsinki, and Chengdu rank of the top cities on the list. When the smart cities are ranked structurally on the list, it is

seen that Mexico City (114), Istanbul (115), Rome (116), Rio de Janeiro (117) and Sao Paulo (118) are at the end of the list.

When the list is examined in detail, it is seen that there are cities which come to the front in both technological and structural terms. The first ones of these cities are Zhuhai and Abu Dhabi. Zhuhai is at the top of the list in terms of technology, while it is ranked as the sixth in terms of structure. Also, Abu Dhabi is at the top of the list in terms of structure, while it is ranked as the eleventh in terms of technology. Another city is Shenzhen, which comes to the front in the technological ranking (2) and is prominent in structural ranking (13). Nanjing included in the list is also seen to be ranked among the top cities when it is about technology (3) and structure (12). Hangzhou included in the list is also seen to be ranked among the top cities both structurally (3) and technologically (5).

6. Conclusion and Evaluation

The main purpose of this study is to rank smart cities both structurally and technologically by using COPRAS and ARAS methods. Within the scope of the study, the SCI (2021) has been used. The index in question has been examined in detail and smart cities have been listed in terms of structural and technological aspects in line with the structure of the report. In the related report, 118 smart cities have been scored structurally and technologically and a general ranking has been made. Within the scope of this study, smart cities have been ranked both structurally and technologically and the results have been evaluated.

Within the scope of the study, five criteria, namely health & safety, mobility, activities, opportunities (work & school) and governance have been weighted to rank 118 alternatives, primarily by using the Entropy weighting method. As a result of the analyzes made, the most important criterion in terms of technology has become governance (C5), while it has become opportunities (work & school) (C4) from a structural point of view. COPRAS and ARAS methods have been used for reasons such as being a simple and easy to apply in ordering the alternatives within the scope of the study. The reason why the method COPRAS is used is the fact that the method also shows the utility of alternatives. One of the important issues that attract attention is that the results obtained according to the ARAS and COPRAS methods are the same. This can be considered as an indication that the analyzes are reliable.

According to the results of the analysis, it is seen that there are differences in the ranking of the cities in terms of technology and structure. In terms of technology, Zhuhai ranks first, followed by Shenzhen, Nanjing, Guangzhou, Hangzhou, Beijing, Shanghai, Chongqing, Tianjin and Chengdu. According to both COPRAS and ARAS methods, Abuja is at the bottom of the list. Abuja is followed by Osaka, San José, Rio de Janeiro, Rome, Lagos, Kiel, Tokyo, Athens, and Bogota.

When the research results are evaluated in terms of structure, Abu Dhabi ranks first, followed by Chongqing, Hangzhou, Dubai, Tianjin, Zhuhai, Guangzhou, Beijing, Helsinki, Chengdu. Sao Paulo is the last city. Sao Paulo is followed by Rio de Janeiro, Rome, Istanbul, Mexico City, Sofia, Athens, Santiago, Nairobi and Bogota. In this case, it can be suggested that the structural features of these cities are low and should be developed. If the results obtained by considering the general ranking in the SCI (2021) report are compared, it is seen that there are deviations according to the report. However, when evaluated both

technologically and structurally, it is thought that the scores in the sub-items of the five criteria affect the ranking and this situation is reflected in the rankings.

Another issue that draws attention within the scope of the study is the technological and structural variability of Bordeaux, Glasgow, Istanbul, Kiel, Lausanne, Leeds, Lille, Medina, San José, which are newly included in the SCI (2021) report. According to COPRAS and ARAS methods, Istanbul (29) ranks first in terms of technology, while Bordeaux (37) ranks first in terms of structure. It is also seen that San José is at the bottom of the list in both groups.

In this study, the research questions have been answered and the same results have been obtained with two different MCDM methods, and different structural and technological rankings have been shown. It is considered that this study will enable the determination of the structural or technological status of smart cities and the necessary improvements and arrangements. It is also considered to be a source in terms of enabling the ranking of smart cities in terms of technology and structure as an alternative to the SCI (2021) report.

This study has some limitations. Within the scope of the study, COPRAS and ARAS methods, which are in the solution of problems in various studies, have been used. However, in addition to these methods, rankings can be made using different MCDM methods to observe how the rankings change according to different scenarios. Different rankings can also be made by adding new ones to the five criteria in SCI (2021), taking into account the structural and technological variables. The detailing of the studies can be suggested by applying the MCDM approaches such as the analytic hierarchic process and analytic network process where expert opinion is taken into account as weighting method. In addition, fuzzy MCDM methods can be used to solve the problem.

Appendix A

Table A1

Decision matrix used in the study

Note: In order to rank smart cities technologically and structurally, the values of five criteria (health & safety, mobility, activities, opportunities (work & school), governance) as C1, C2, C3, C4 and C5 have been calculated using arithmetic averages.

Cities	Technologies					Structures				
	C1	C2	C3	C4	C5	C1	C2	C3	C4	C5
Abu Dhabi	75.0333	72.0800	87.5000	77.8750	71.9750	74.1167	74.1500	82.5500	72.4400	70.5750
Abuja	33.0333	38.9200	64.4000	55.4750	32.1000	37.8500	33.2000	64.8000	50.1000	29.8250
Amsterdam	54.4000	53.7800	75.8000	60.7750	50.9000	53.7167	52.8500	66.3000	65.2200	58.4500
Ankara	64.5500	60.0000	73.2000	66.4500	57.5250	57.9000	48.6500	62.3000	59.5800	58.9500
Athens	45.5333	42.5400	80.9000	51.2500	38.7250	36.7833	22.2000	49.4000	35.2400	29.4750
Auckland	57.8500	49.6400	76.8000	64.1000	53.5000	60.8333	35.1500	77.8500	66.8600	61.4750
Bangkok	64.0000	62.0200	75.6000	72.9750	62.1250	52.9667	30.6000	58.2500	56.7200	41.6500
Barcelona	51.1167	53.9200	76.8000	59.7500	48.5750	47.1833	45.4000	68.5500	59.8200	42.4750
Beijing	80.3167	78.9800	90.9000	84.1250	78.8250	68.2000	48.6500	79.3000	76.9200	69.6250
Bengaluru	62.7833	65.0200	77.8000	74.6000	62.9000	53.0000	41.8500	70.9500	69.8400	53.5750
Berlin	47.5667	47.7200	72.6000	51.5750	45.5750	54.2167	46.6500	44.1500	57.2200	52.9500
Bilbao	55.9500	56.7200	82.7000	64.0500	52.1250	61.9167	65.1000	78.9500	68.3200	55.1500
Birmingham	52.4333	46.6400	72.3000	59.7000	47.4750	47.5333	34.9000	66.7000	59.0200	48.9000
Bogota	46.4167	45.6000	71.9000	51.8750	37.7500	30.4167	20.7000	65.2000	37.6000	31.2750
Bologna	58.7500	52.4800	82.9000	56.9000	48.4250	63.3833	48.0500	79.2000	56.6200	51.0000
Bordeaux	53.7333	55.8600	76.4000	61.6750	49.0250	48.9167	43.7500	84.1000	63.7800	46.4000
Boston	47.7667	46.8800	75.6000	57.4250	47.0000	52.9333	31.8000	73.7500	65.4800	56.6750
Bratislava	53.6333	46.4200	76.3000	59.7500	46.5500	46.1833	29.6000	53.4000	60.4200	43.8000
Brisbane	56.7667	47.6600	77.1000	59.4500	47.0000	60.5833	41.4000	75.9000	67.2400	55.7500
Brussels	50.3167	48.7400	71.7000	55.4750	45.9000	50.2000	43.1500	71.9000	56.3600	46.0000
Bucharest	53.8500	48.5600	73.6000	58.3250	39.2750	33.8000	22.7000	56.4000	51.1000	29.4250
Budapest	49.9333	51.3400	77.8000	60.4000	45.4750	40.0333	37.5500	60.7000	47.0600	38.8750
Buenos Aires	49.9833	56.1400	77.0000	50.3750	45.9500	35.7833	34.8000	76.4500	41.7600	37.1250
Busan	65.7500	52.1200	71.0000	54.7250	54.2750	58.7833	48.1000	53.2500	50.7800	48.8000
Cairo	53.2167	58.1400	70.6000	59.1000	51.5250	40.2000	30.5000	50.8000	44.4600	40.1750
Cape Town	51.1000	51.0200	78.8000	57.8000	46.0500	40.1833	37.4000	67.0000	45.8600	39.6500
Chengdu	75.7333	79.2200	88.9000	80.0750	71.7750	68.6500	55.1000	80.4500	72.6200	61.2000
Chicago	49.6500	54.1200	72.6000	57.4000	48.9250	45.0500	40.8500	69.0500	57.6800	49.1500
Chongqing	80.2167	77.5400	89.1000	82.0000	76.6500	75.8667	62.2000	81.2500	76.4200	69.5750
Copenhagen	55.0667	50.4600	77.7000	63.2250	51.3750	62.1333	53.0000	79.1000	73.1000	63.7750
Denver	50.6333	47.8000	76.6000	56.9500	49.5250	47.0667	37.5000	73.6000	65.2400	56.1500
Dubai	73.9167	68.2600	85.9000	76.5500	69.1000	73.7667	64.6500	80.4500	71.1800	71.1250
Dublin	46.8000	49.0200	77.2000	61.9750	44.4000	45.6000	36.0500	69.8000	66.0800	51.2750
Dusseldorf	51.2500	52.6600	73.9000	57.4500	50.6250	59.4500	49.8000	71.7000	62.1400	56.4750
Geneva	55.9167	49.7400	73.1000	59.3750	50.8750	63.0333	52.2000	81.7500	64.8200	65.0500
Glasgow	58.5833	43.7000	65.7000	59.2500	44.9750	48.9500	43.7000	69.7500	61.1400	46.9500
Gothenburg	48.3167	48.6800	77.1000	57.9750	41.8000	51.9667	43.1000	78.3000	64.0200	52.5750
Guangzhou	82.4000	79.6600	92.0000	86.0250	80.2250	70.0333	52.1500	80.9500	76.7800	68.2000
Hamburg	50.3167	49.9400	72.9000	54.1000	43.8000	56.0833	46.3500	76.0000	62.9000	54.4750
Hangzhou	81.4333	81.4800	89.7000	84.6500	77.9000	74.6833	59.5500	83.0500	78.9000	68.5500
Hanoi	70.2500	67.1000	82.6000	79.8500	68.7500	63.2000	36.4000	66.8500	75.1200	61.7000
Hanover	44.5833	47.8000	71.0000	50.9750	43.2250	58.7333	55.3000	73.8000	67.0600	51.6250
Helsinki	57.9000	52.0200	74.8000	67.0250	49.9000	62.4333	66.6000	77.3500	69.2400	59.4000
Ho Chi Minh City	69.6167	66.2000	80.4000	79.2500	66.5500	61.7667	39.3000	69.4000	77.8600	61.5000
Hong Kong	58.5000	52.7800	74.9000	70.4000	52.8000	46.9000	41.9000	50.4500	59.8400	45.2750
Hyderabad	61.9333	64.1200	77.6000	73.2250	62.2500	55.7500	49.1000	70.7500	68.5200	55.3250
Istanbul	65.7667	60.8800	79.9000	62.7250	55.4500	36.2167	5.8000	39.3500	28.2000	42.9000
Jakarta	67.4333	68.3200	80.4000	75.2000	66.1750	50.8167	39.9000	66.4500	67.0600	38.3500
Kiel	43.9000	42.3000	64.2000	44.9000	42.4750	57.7667	29.9500	68.5500	58.7600	43.4500
Kiev	54.3167	56.7800	83.0000	66.0250	52.6500	28.9000	34.5000	69.2500	59.8600	14.2750
Krakow	58.8000	49.0400	76.9000	60.4750	51.9000	42.0333	42.5500	68.4500	63.6200	52.2000
Kuala Lumpur	58.4667	59.3000	79.4000	66.5750	55.2250	53.3000	41.4500	27.1500	66.2600	47.7750
Lagos	38.4833	44.3800	73.6000	58.3250	33.1250	33.5000	23.7000	60.3500	46.0800	27.8250
Lausanne	53.2333	50.7800	78.5000	64.7500	50.2250	64.9000	16.5500	84.6500	58.8600	47.3250
Leeds	56.6000	46.6000	72.9000	62.2000	52.8000	48.6333	40.3000	67.1500	64.2600	27.2000
Lille	55.2167	55.7400	73.3000	61.1750	47.9000	47.4167	31.2500	74.2000	57.1800	46.2750
Lisbon	54.8667	46.3400	82.3000	66.0000	49.8250	43.4667	29.2500	73.0500	40.6000	36.1250
London	55.5500	54.6600	75.3000	63.8500	53.5750	47.9500	32.1500	39.4000	63.1600	38.0000
Los Angeles	57.9667	57.3800	76.6000	63.5500	59.5250	48.8500	39.5500	36.9500	50.4600	43.6250
Lyon	56.4667	53.8800	79.1000	58.5750	48.4250	34.8833	45.8500	80.7000	47.6400	38.6750

Cities	Technologies					Structures				
	C1	C2	C3	C4	C5	C1	C2	C3	C4	C5
Madrid	59.0000	61.8400	80.5000	64.2750	53.0500	48.2333	42.1000	75.9500	50.4800	49.7750
Makassar	59.1000	58.2000	64.8000	67.9500	58.5750	50.9667	28.3500	62.5000	56.1000	51.8750
Manchester	53.0833	44.9200	72.5000	61.9750	48.2500	53.3667	42.3000	69.5500	61.6600	43.5750
Manila	56.3333	63.3000	73.1000	67.1000	58.4250	33.7333	24.9000	60.0000	58.1200	33.2750
Marseille	53.5667	49.7800	72.6000	56.9750	41.7750	36.3333	38.0500	64.6000	51.0000	39.0750
Medan	62.1000	60.1600	69.2000	70.3500	60.4250	34.3000	42.8000	61.1500	48.8600	48.9000
Medellin	62.6167	58.2400	72.6000	62.3750	48.9750	46.0333	50.0500	77.4500	54.7200	41.6750
Medina	57.2333	59.0200	69.9000	63.4250	65.3250	45.9000	18.2000	56.6500	58.3200	54.7000
Melbourne	57.8500	49.0400	77.7000	63.2500	50.5500	53.6000	39.2000	75.4000	52.6400	53.8500
Mexico City	47.7667	52.2400	74.5000	53.1750	45.4500	28.8833	23.6000	61.5000	22.6600	33.6000
Milan	57.1333	53.3000	81.1000	54.5000	49.2500	57.9833	39.8500	70.0000	40.7000	42.5250
Montreal	50.8833	49.7800	77.0000	61.1500	44.2250	55.3167	39.5000	76.1000	68.6600	40.8000
Moscow	64.8500	61.6200	81.4000	69.8250	60.1750	55.1000	48.8500	35.8500	62.2400	40.6250
Mumbai	66.7333	68.2800	80.8000	75.5750	67.8500	31.4333	43.6000	27.9500	54.6600	57.0750
Munich	51.4667	53.1200	76.8000	56.7250	47.9500	48.0667	48.8000	78.3000	37.9200	45.1250
Nairobi	40.7333	40.4400	72.7000	63.1250	41.2000	31.5167	24.9000	58.7500	44.3800	24.5250
Nanjing	82.4000	84.0800	88.1000	85.0000	78.9750	63.6833	68.1500	41.9500	79.7200	71.9500
New Delhi	68.6333	67.0800	78.1000	72.2250	69.6750	52.6833	48.1000	68.1500	53.0400	45.5750
New York	59.4000	61.5400	79.4000	64.2000	57.4750	24.2500	41.9000	71.9500	64.7200	54.3750
Newcastle	53.7833	43.2000	72.0000	61.4250	47.3500	59.4167	50.8000	75.1000	66.7400	56.0500
Osaka	45.9333	37.9000	53.3000	42.9500	31.1750	58.3833	52.0500	47.7000	48.2000	24.7250
Oslo	55.2000	55.8200	76.3000	62.7500	49.0000	54.7833	61.6000	80.0000	72.4000	63.5250
Paris	56.5500	53.5000	77.0000	56.1500	48.0500	30.1667	39.8000	73.6500	31.0200	35.7250
Philadelphia	49.6333	46.0800	69.7000	50.0500	48.1250	40.3333	35.1500	64.2000	31.4600	45.5250
Phoenix	50.0667	41.5800	74.2000	55.8000	42.4500	48.7333	36.3000	63.4000	63.9000	30.7250
Prague	58.9833	48.0000	81.7000	62.4500	48.8250	48.2667	43.6000	65.8000	59.0000	49.7500
Rabat	48.2500	48.2800	71.5000	59.4750	46.5500	37.5667	41.7000	34.1500	39.2000	29.1750
Rio de Janeiro	33.3833	47.8800	76.1000	41.3750	36.7500	25.3833	17.9000	58.1000	21.3800	8.4500
Riyadh	71.6833	66.9200	79.3000	74.5250	66.7500	64.2333	46.6500	68.4000	55.4400	63.6500
Rome	44.5500	39.7600	74.7000	43.5750	37.9250	22.9167	17.2000	60.3000	22.5200	28.9000
Rotterdam	54.7833	47.8800	72.4000	57.3750	49.3000	52.9333	51.9500	27.3500	61.9600	41.0500
San Francisco	49.7333	52.0400	71.8000	56.8500	47.0750	37.5167	35.1000	32.3500	60.7200	55.4750
San José	43.1500	41.3800	70.1000	47.5750	31.5500	44.8167	23.7000	61.4500	46.2800	26.8250
Santiago	49.3500	46.1000	73.9000	56.4250	38.2500	27.6167	25.3500	55.3500	38.9400	31.1750
Sao Paulo	39.7667	50.5800	72.8000	54.5500	42.9500	21.4000	17.9500	31.3500	26.3000	27.5750
Seattle	51.3333	49.7000	75.0000	58.4750	47.3000	36.5500	34.5000	73.8000	66.2000	55.0750
Seoul	68.6167	59.6000	77.7000	65.0250	59.4000	30.7333	11.6500	62.5500	51.9200	47.4000
Shanghai	80.8333	79.4000	90.6000	85.1000	76.7250	68.3333	47.6000	80.6000	60.5200	66.0750
Shenzhen	83.5833	82.6600	88.9000	85.2250	80.7000	75.4833	62.7500	81.6500	62.3200	50.9250
Singapore	72.9833	61.5000	83.5000	76.4250	61.6000	69.9167	62.7500	39.1500	58.5000	68.5750
Sofia	50.9667	43.8800	76.4000	61.5500	37.7250	25.9500	31.7500	56.9000	38.6200	17.4750
St. Petersburg	58.1833	53.4600	85.2000	67.7250	55.7750	41.0000	43.8500	74.7500	46.3600	31.8000
Stockholm	52.2167	45.4600	77.2000	58.2250	42.6000	36.8667	44.2000	38.1500	65.1200	57.5500
Sydney	58.7333	50.4200	76.0000	60.8250	51.4750	26.6833	39.8000	70.8500	67.1000	54.4750
Taipei City	72.3500	68.0400	84.9000	66.4000	68.8500	66.0000	44.4500	66.9000	52.2200	48.9000
Tallinn	56.9500	41.8000	87.3000	67.2250	59.5500	55.1667	13.1000	81.0000	68.3000	48.5000
Tel Aviv	58.0333	51.5400	80.2000	62.2750	51.3000	47.5833	28.2000	66.7500	61.0400	34.2000
The Hague	53.2167	46.0200	70.7000	58.5750	49.0250	56.1333	52.6000	71.1500	66.2000	56.4500
Tianjin	81.1167	80.6200	89.6000	82.6750	71.7750	72.3000	62.4000	79.9500	75.3800	62.7750
Tokyo	50.2667	45.8800	62.6000	48.2000	34.7250	46.3833	52.0000	31.2500	42.3000	27.2500
Toronto	52.4667	49.7800	77.5000	59.2250	51.8500	54.3167	36.5000	33.8500	66.3400	58.7750
Vancouver	53.3833	47.4800	73.3000	61.1750	46.8250	41.4167	42.6000	76.2500	67.7400	42.1000
Vienna	52.4833	49.5600	80.9000	60.7250	46.4000	58.5500	58.5000	79.9000	66.7600	40.9500
Warsaw	59.9667	55.5400	80.2000	65.4000	55.7250	39.1000	14.7000	71.8500	64.7800	53.0000
Washington D.C	53.2667	55.2800	73.1000	58.1250	51.9250	44.5167	43.5000	75.3000	62.8400	57.0000
Zaragoza	52.7333	52.4800	85.1000	63.5000	46.9750	61.6000	26.4500	38.7500	65.6200	48.4500
Zhuhai	85.3167	85.7000	90.4000	87.3500	85.8500	84.0333	80.2000	44.3000	67.9000	62.2750
Zurich	52.7667	55.1000	78.5000	66.5500	50.7750	70.7833	60.1000	78.2500	74.4400	53.1500

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