Rađenović, Ž., & Boshkov, T. (2023). Smart cities sustainability achievements ranking: PCA weighting, *SCIENCE International journal, 2*(4), 141-146.
doi: 10.35120/sciencej0204141r UDK: 711.45:004.78]502.131.1:519.2(4-672EU)

SMART CITIES SUSTAINABILITY ACHIEVEMENTS RANKING: PCA WEIGHTING

Žarko Rađenović[1], Tatjana Boshkov[2]*

[1]Innovation Center University of Niš, Serbia, e-mail: z_radjenovic89@outlook.com
[2]Faculty of Tourism and Business Logistics, Goce Delcev University –Stip, N. Macedonia,
e-mail: tatjana.boskov@ugd.edu.mk

Abstract: Cities all over the world are looking for dependable and sustainable growth solutions as a consequence of expansion of citizen demands, ecological issues, and technology advancements. Comprehending the notion of smart cities requires understanding its fundamental multiple dimensions. Regarding the complexity of smart cities, a multilayered framework incorporating social inclusion, environmental sustainability, and inclusive economic growth is required. Six fundamental aspects of smart cities are identified by researchers: people, transportation, living, government, environment, and economics. Moreover, the main goal of developing smart cities is to use information technology to increase urban sustainability. In order to evaluate how well European cities have the capacity to change according to the requirements of their population, the aim of this study is to ensure an aggregate rating of smart city performance based on citizens' needs. The research creates an important contribution by offering an extensive framework to measure smart cities' urban performance using the multi-criteria ARAS (Additive Ratio Assessment) decision-making method. The analysis additionally provides a contribution by identifying the key smart cities' indicators that have the greatest impact on Aalborg's optimal urban performance achievement, making it the best-ranked, smart liveable and Danish sustainability „flagship" city.

Keywords: Smart cities, Sustainability, Ranking, Principal Component Analysis.
Field: Social Sciences and Humanities

1. INTRODUCTION

The growth of the urban population that characterizes the last decades has imposed numerous challenges on modern society, where one of the biggest challenges can be identified as the necessity of meeting the growing needs of the urban population while ensuring economic, environmental and social sustainability of the society. The increase in urbanization together with the consequences of human activities in existing cities caused an increase in interest in sustainable urban planning and development (Zheng et al, 2020). Nevertheless, the growth of urban areas puts the problem of scarcity of resources at the forefront, especially in the context of the growing needs of the urban population. Additionally, the consequences of rapid urbanization are reflected in the impairment of urban resilience through endangering the quality of life of inhabitants, due to increased environmental pollution and inadequate infrastructure solutions, which do not provide acceptable living conditions (Williams et al., 2019). The aforementioned problems lead to a violation of one of the basic functions of cities – livability (Verma & Raghubanshi, 2018). Bearing the above in mind, it can be concluded that urban sustainability functions as a central issue in achieving economic, social and environmental sustainability (Verma & Raghubanshi,2018). However, when creating development strategies, policymakers often overlook the opinions of inhabitants. In order to achieve sustainable urban development and increase the attractiveness and competitiveness of cities, it is necessary to examine different aspects of citizens' perceptions. Therefore, this research aims to propose a composite index of smart city performance based on citizens' perceptions, in order to assess the adaptability of European cities to the needs of their residents. The paper's contribution is reflected in the provision of a comprehensive framework for evaluating the urban performance of smart cities, which is based on the evaluations of residents. In addition, another contribution of the paper is the identification of the main dimensions of smart cities that have the greatest influence on the achieved urban performance.

2. MATERIALS AND METODS

The methodological framework is based on creating sustainable smart cities composite indicators based on the latest available data from the Eurostat Database, for selected European cities. The following indicators/criterias (C) are: Public transport in the city, for example bus, tram or metro (C1), Green spaces

*Corresponding author: z_radjenovic89@outlook.com

such as public parcs or gardens (C2), Sports facilities such as sport fields and indoor sport halls in the city(C3), Cultural facilities such as concert halls, theatres, museums and libraries in the city (C4), In this city it is easy to find a good job (C5), In this city it is easy to find good housing at a reasonable price(C6), Public spaces in this city such as markets, squares, pedestrian areas(C7), Generally speaking most people in this city can be trusted(C8), The quality of the air in the city (C9), The noise level in the city (C10), The cleanliness in the city (C11), Most people in my neighbourhood can be trusted (C12), Your personal job situation (C13), The financial situation of your household (C14), The life you lead (C15). The Principal Component Analysis (PCA) method will be used to create the aforementioned indicators, and then the weighting coefficients for each indicator will be determined. In order to determine the most smart, sustainable, and livable alternative, European cities will be ranked using the ARAS (Additive Ratio Assessment) multi-criteria decision-making process. Selected European cities are: Bruxelles, Antwerpen, Liège, Sofia, Burga, Praha, Ostrava, København, Aalborg, Berlin, Hamburg, München, Köln, Frankfurt am Main, Essen, Stuttgart, Leipzig, Dresden, Dortmund, Düsseldorf, Nürnberg, Darmstadt, Freiburg im Breisgau, Augsburg, Karlsruhe, Saarbrücken, Koblenz, Rostock, Konstanz, Mannheim. Composite indicators are useful monitoring tools for multi-layered situations and are often created using multi-criteria decision-making (MCDM) methods. (Mendola & Volo, 2017). In addition to building the composite index, a variety of multi-criteria procedures should be used to ensure appropriate evaluation and examination. The aforementioned approaches have shown to be quite successful, and any thorough evaluation process must include them: TOPSIS (Nilashi et al. 2019; Kwok & Lau, 2019), AHP (Zhou et al., 2015), PROMETHEE (Lopes et al., 2018; Ostovare & Shahraki, 2019). The following phases are involved in the ARAS MCDM technique:

• For the first phase, a formula that occurs the selection of matrix into consideration is used to establish the reference point A0. In contrast to previous approaches, the ARAS technique presents the most beneficial option, A0, which is chosen in accordance with the decision-makers' opinions.

• The second phase is based on the normalized reference point value, which is assigned to create a normalized matrix. Either the sum approach or the linear method is applied for normalizing.

• The weighted normalized matrix values for each option Ai and the reference point A0 are added together during the aggregation procedure. Researchers derive the overall performance indices of Si and S0, where Si denotes the ith alternative's total performance index and S0 denotes the best alternative's total performance index.

$$S_i = \sum_{j=1}^{n} y_{ij}$$

• Calculating the degree of usefulness:

$$U_i = \frac{S_i}{S_0}$$

• Alternatives are ranked in ascending order based on Ui values. The top-rated option A*ARS, as per the ARAS method, the following formula can be used to define it.:

•

$$A^*_{ARS} = \{A_i | A_i = maxU_i\}$$

Principal Component Analysis appropriateness is often assessed using two formal tests: Bartlett's test and KMO (Kaiser-Meyer-Olkin sample adequacy measure) statistics. In the first test, the Chi-square statistic is employed to see if there is a substantial connection between the initial variables. A larger statistical significance suggests a lower likelihood of the null hypothesis being true. Table 3's data demonstrates that a threshold for significance of 0.000 can be used to reject the null hypothesis. KMO compares the observed correlation coefficients with partial coefficients, and should be at least 0.5. Given the KMO value of 0.914 in this instance, factor analysis should be used as indicated.

Table 1. KMO and Bartlett's Test for PCA

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.914
Bartlett's Test of Sphericity	Approx. Chi-Square	1841.009
	df	105
	Sig.	.000

The following procedure in factor analysis is to rotate each factor by giving them specific weights after the most important components have been determined. Only variables having weights more than 0.3 are selected. Following that, an orthogonal factor rotation process called the Varimax approach is applied. A matrix of factors is created after numerous factor rotations. The factors with greater weight scores for each individual factor are highlighted in this matrix (Table 2).

Table 2. Varimax rotation

Rotated Component Matrix[a]			
	Component		
	1	2	3
C8	.870		
C12	.865		
C9	.783	.356	
C10	.757	.539	
C15	.683	.367	.560
C14	.677		.623
C2	.357	.824	
C7	.418	.816	
C1		.804	
C4		.749	.439
C3	.432	.748	
C11	.580	.626	
C6			-.840
C5		.326	.790
C13	.582		.693
Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalization.[a]			
a. Rotation converged in 5 iterations.			

Techniques for assessing weight are essential for resolving issues where there are several factors for making decisions. The subsequent stage of the study in this work is to create weights from the factor loadings matrix following rotation. The percentage of an indicator's total variation that may be attributed to a factor is shown by the square of the factor loadings. Weights will be computed using the rotating loadings estimations. According to Nardo et al. (2005), weights are the normalized squared factor loading, which is the variance of the first component that variable C1 can explain (Table 3).

Table 3. Calculation of weights based on variance

Variables	Component 1		Component 2		Component 3	
	Loadings	Weights of variables within Component 1	Loadings	Weights of variables within Component 2	Loadings	Weights of variables within Component 3
C1			0.804	**0.184**		
C2			0.824	**0.193**		
C3			0.748	**0.159**		
C4			0.749	**0.160**		
C5					0.790	**0.344**
C6					-0.840	**0.389**
C7			0.816	**0.190**		
C8	0.870	**0.209**				
C9	0.783	**0.169**				
C10	0.757	**0.158**				
C11			0.626	**0.112**		
C12	0.865	**0.207**				
C13					0.693	**0.265**
C14	0.677	**0.127**				
C15	0.683	**0.129**				
	3.61		**3.50**		**1.81**	
VAR of pre-calculated variables weights within components	**0.683**					

Table 4. Weighting coefficients for analyzed indicators

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	C15
w_i	0.05	0.054	0.037	0.037	0.174	0.222	0.053	0.063	0.041	0.037	0.018	0.063	0.103	0.024	0.024

doi: 10.35120/sciencej0204141r UDK: 711.45:004.78]502.131.1:519.2(4-672EU)

2.RESULTS AND DISCUSSION

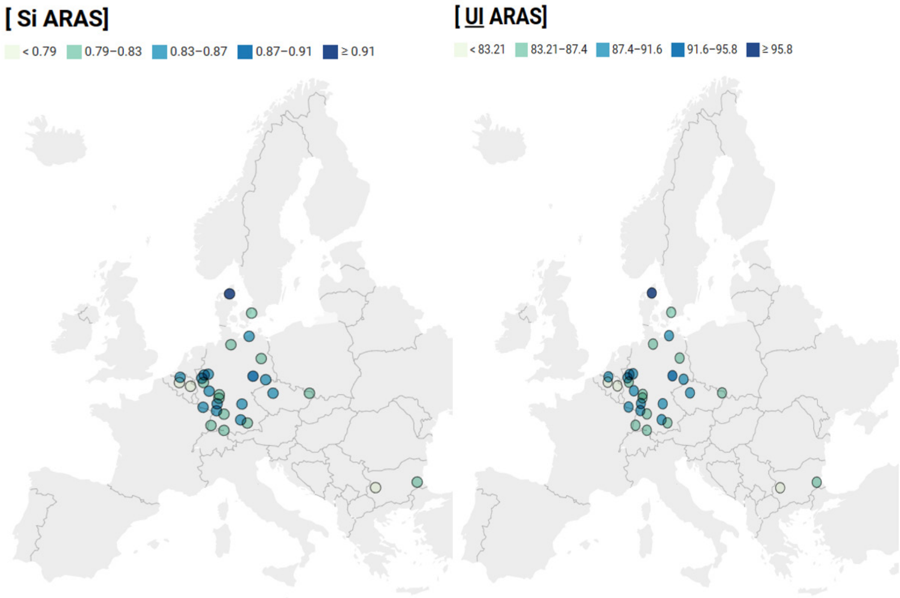
Because different approaches are taken to determine the weighting coefficients, different European cities are ranked differently when utilizing the ARAS technique. By converting sustainable indicators into factors based on loading values, PCA is applied. Afterwards, using variance, the weights are computed for each variable independently, initially inside the component that they compose. Based on the entire performance index and degree of usefulness in the ARAS technique, Aalborg is ranked as the most beneficial smart city option out of the thirty cities that were studied, as shown in Table 5. Conversely, the least desirable option for a livable smart city is Bruxelles.

Table 5. Final ranking ARAS/PCA

Smart Cities	Si:ARAS	Ui:ARAS	Final Ranking ARAS/PCA
Bruxelles	0.7518	79.0073	30
Antwerpen	0.8576	90.1261	8
Liège	0.7856	82.5568	28
Sofia	0.7845	82.4401	29
Burgas	0.8276	86.9689	18
Praha	0.8349	87.7402	15
Ostrava	0.8175	85.9092	23
København	0.8312	87.3478	16
Aalborg	0.9516	100.0000	1
Berlin	0.7999	84.0632	26
Hamburg	0.8260	86.8006	20
München	0.8273	86.9391	19
Köln	0.7967	83.7224	27
Frankfurt	0.8095	85.0639	24
Essen	0.8433	88.6167	14
Stuttgart	0.8289	87.1105	17
Leipzig	0.8989	94.4656	2
Dresden	0.8665	91.0539	3
Dortmund	0.8518	89.5164	11
Düsseldorf	0.8508	89.4078	12
Nürnberg	0.8548	89.8335	10
Darmstadt	0.8238	86.5760	22
Freiburg	0.8259	86.7904	21
Augsburg	0.8607	90.4539	5
Karlsruhe	0.8578	90.1486	7
Saarbrücken	0.8610	90.4835	4
Koblenz	0.8582	90.1901	6
Rostock	0.8439	88.6888	13
Konstanz	0.8048	84.5702	25
Mannheim	0.8568	90.0433	9

Total performance index and the level of usefulness in the ARAS MCDM method are depicted in the following European cities map chart (Figure 1) with a linear five-coloured values scale, where it could be concluded that the Danish Aalborg (dark blue circle) is the optimal alternative.

Figure 1. Si ARAS and Ui ARAS after matrix normalization for selected European smart sustainable cities



3. CONCLUSION

In order to increase the city's appeal, the smart living dimension refers to livability circumstances that are improved by procedures meant to enhance people' general well-being. Initiatives to provide appropriate quality of health and educational services, as well as to improve the material situations of citizens, are some of these procedures. The outcomes of the research greatly rely on the chosen indicators, and utilizing other indicators may result in varying conclusions. Furthermore, the weights assigned to the criteria have an important impact on the alternatives ranking, and using different methods to determine the weights can lead to a reversal in ranking. Initiatives aimed at enhancing city transportation, cutting down on traffic and commute times, and guaranteeing adequate accessibility to every area of the city through the use of technology are all included in the concept of smart mobility. Due to Aalborg's remarkable 15-rank leap, the northern Danish city was placed fifth in the "Leadership in Sustainability" category and third in the "Best Improver" category according to GDS (Global Destination Sustainability) index. SMART Aalborg is an integrated approach to create growth and support sustainable and technological development throughout the municipality of Aalborg. The findings of the investigation are primarily determined by the indicators used in this research. Using alternative indicators could deliver distinct findings. Moreover, the weights assigned to the variables have an important influence on the rankings of the alternatives. Hence, using various techniques for determining the weights could end up in a rank reversal. Using multi-criteria decision-making techniques like VIKOR, CRITIC, TOPSIS, and others, the creation of composite indicators and the calculation of their weight coefficients is another important component that might enhance future study in this field. Additionally, it is required to rank various cities according to the use of particular solutions for finding out leaders in this field with optimal values of the composite indicators for implementing smart cities concept. AHP, PAPRIKA, FUCOM, MOORA, COPRAS, CoCoSo, and other multi-criteria decision-making techniques, along with sufficient sensitivity analyses, can greatly aid in the development of a strategic framework for discovering out the public cost of cities sustainability by ranking research objects.

ACKNOWLEDGEMENT

This research was financially supported by the Ministry of Science, Technological Development and Innovation of the Republic of Serbia (Contract No. 451-03-47/2023-01/ 200371).

REFERENCES

Kwok, P. K., & Lau, H. Y. (2019). Hotel selection using a modified TOPSIS-based decision support algorithm. Decision Support Systems, 120, 95-105.

Lopes, A. P. F., Muñoz, M. M., & Alarcón-Urbistondo, P. (2018). Regional tourism competitiveness using the PROMETHEE approach. Annals of Tourism Research, 73, 1-13.

Mendola, D., & Volo, S. (2017). Building composite indicators in tourism studies: Measurements and applications in tourism destination competitiveness. Tourism Management, 59, 541-553.

Nardo, M., Saisana, M., Saltelli, A., & Tarantola, S. (2005). Tools for composite indicators building. European Comission, Ispra, 15, 19-20.

Nilashi, M., Samad, S., Manaf, A. A., Ahmadi, H., Rashid, T. A.,

Munshi, A., ... & Ahmed, O. H. (2019). Factors influencing medical tourism adoption in Malaysia: A DEMATEL-Fuzzy TOPSIS approach. Computers & Industrial Engineering, 137, 106005.

Ostovare, M., & Shahraki, M. R. (2019). Evaluation of hotel websites using the multicriteria analysis of PROMETHEE and GAIA: Evidence from the five-star hotels of Mashhad. Tourism Management Perspectives, 30, 107-116.

Verma, P. & Raghubanshi, A.S. (2018) Urban Sustainability Indicators: Challenges and Opportunities. cological Indicators, 93, 282–291, doi:10.1016/j.ecolind.2018.05.007

Williams, D.S., Máñez Costa, M., Sutherland, C., Celliers, L. & Scheffran, J. (2019) Vulnerability of Informal Settlements in the Context of Rapid Urbanization and Climate Change. Environ. Urban, 31, 157–176, doi:10.1177/0956247818819694.

Zheng, C.,Yuan, J., Zhu, L., Zhang, Y. & Shao, Q. (2020) From Digital to Sustainable: A Scientometric Review of Smart City Literature between 1990 and 2019. J. Clean. Prod., 258, 120689, doi:10.1016/j.jclepro.2020.120689

Zhou, Y., Maumbe, K., Deng, J., & Selin, S. W. (2015). Resource-based destination competitiveness evaluation using a hybrid analytic hierarchy process (AHP): The case study of West Virginia. Tourism Management Perspectives, 15, 72-80.