A Compact Sustainable Smart City Assessment Framework: A Comparative Analysis of European Cities

MERT UNAL, MEHTAP DURSUN
Industrial Engineering Department
Galatasaray University
Cıragan Caddesi, No:36 34349, Ortakoy, Istanbul
TURKIYE

Abstract: - This study proposes a composite sustainable smart city (SSC) index based on 17 indicators grouped into four dimensions and applies it to nine European cities using 2018 data. It examines how weights derived using Redundancy-Penalized Entropy Weighting (RPEW), the Analytic Hierarchy Process (AHP), and the Analytic Network Process (ANP) affect the resulting city scores and rankings. RPEW is an objective method that derives weights from entropy-based variation across cities and adjusts for redundancy among correlated indicators. AHP and ANP are judgment-based, subjective methods. AHP derives indicator and dimension priorities from pairwise comparisons within a hierarchy, while ANP accounts for interdependencies among indicators through a network structure. The pairwise judgments used for AHP and ANP in this study were collected from three domain experts. To isolate the effect of the weighting approach, the same winsorization, normalization, aggregation, and scoring procedures were applied across all three methods. Stockholm ranks first under RPEW and AHP, while Amsterdam ranks first under ANP. Spearman's rank correlations range from 0.783 to 0.933, showing that the rankings are strongly related while still differing in the positions of some cities. Overall, the results illustrate how objective data patterns, hierarchical judgments, and indicator interdependencies can lead to different assessments of city performance.

Key-Words: - Sustainable Smart City, Composite Index, Redundancy-Penalized Entropy Weighting, Analytic Hierarchy Process, Analytic Network Process, Indicator Interdependence, City Ranking

Received: March 21, 2026. Revised: May 22, 2026. Accepted: September 9, 2026. Published: November 12, 2026.

1 Introduction

People, jobs, housing, economy, transport, and public services are the key elements of a city. Union of these elements creates opportunities. However, it also puts pressure on natural resources, the environment, and residents' quality of life. Therefore, a city must be sustainable. But being sustainable is not enough. It also needs to consider economic vitality, social equity, health, and the conditions of life for future generations. Although the term *sustainable city* has been used by the researchers in different ways, there is no single definition that captures every aspect of it [1].

Following the sustainable city concept the *smart city* concept emerged. This concept emerged with a focus on the use of information and communication technologies, data, and connected infrastructure to improve urban services and management. These tools can support areas such as transport, public services, and resource management. However, adopting technology does not by itself make a city smart [2].

The sustainable smart city (SSC) concept addresses these concerns by considering the role of technology in improving urban services and managing city systems. At the same time, environmental, economic, and social outcomes remain central to the assessment. Technology is therefore viewed as a tool for supporting urban sustainability rather than an indicator of sustainable performance on its own. Assessing SSC performance requires a multidimensional approach that considers both the outcomes achieved by cities and the methods used to measure and combine them [3].

Academics, international organizations, companies have developed indices to assess, score and compare city performance. Indices consist of different dimensions and indicators under these dimensions. They also differ in their purpose, methodology and data sources. Some of them focus on technology and urban competitiveness. Others give attention to environmental and social dimensions. Differences in indicator selection, weighting, and aggregation procedure can therefore lead to different scores and rankings for the same city [4-7].

Composite indices provide a way to bring multiple indicators together, but their results depend on the choices made at each stage of construction. Weighting is especially consequential because it determines how much each indicator contributes to the overall assessment. Objective methods derive weights from the data, whereas judgment-based methods reflect assessments of relative importance. Redundancy-Penalized Entropy Weighting (RPEW) uses variation across cities to estimate the information provided by each indicator and adjusts for redundancy among correlated indicators [8]. The Analytic Hierarchy Process (AHP) derives indicator and dimension priorities from pairwise comparisons within a hierarchy [9]. The Analytic Network Process (ANP) also uses pairwise comparisons but represents influence relationships among indicators in a network and incorporates them into global priorities through the super matrix procedure [10].

These differences are important in SSC assessment because indicators can be related to each other. For example, mobility conditions may affect environmental outcomes. Economic and governance conditions may influence a city's ability to provide services and infrastructure. That is why, when these relationships are considered, the weight of each criterion may change. However, comparing results from different studies is difficult when they use different cities, data years, indicators, or scoring methods. When several aspects of the assessment vary, it is difficult to determine how much of the difference in city rankings can be attributed to the weighting method.

Our study proposes a composite SSC index which is consist of 17 indicators grouped into four dimensions. The case study applies it to nine European cities using 2018 data. During the case study section RPEW, ANP and AHP methods are used as weighting procedure to see how the weighting methodology affect the final scoring and ranking Beside the weighting procedure, The same winsorization, normalization, aggregation, and scoring procedures are used across all three analyses. The weighting method is the only part that changes. The AHP and ANP pairwise judgments used in this analysis were collected from three domain experts specializing in urban sustainability and smart city management.

The study addresses three research questions:

1. How do RPEW, AHP, and ANP differ in the importance they assign to the 17 indicators and four dimensions?
2. How does the choice of weighting method affect city scores and rankings when normalization, aggregation and scoring steps are the same?
3. How consistent are the city rankings across the three methods, and which cities show the greatest rank variation?

Section 2 reviews the literature on SSC assessment and weighting methods. Section 3 explains the index structure, the three weighting methods, and how city scores are calculated. Section 4 presents the results for RPEW, AHP, and ANP and compares the scores and rankings of the cities. Section 5 discusses the main findings and their implications. Section 6 concludes the study by addressing its limitations and suggesting areas for future research.

2 Literature Review

Smart and sustainable city assessment frameworks examine urban performance from different perspectives. Several organizations have developed indices to evaluate cities based on different dimensions and criteria. For example, the IESE Cities in Motion Index [6] includes governance, mobility and transportation, environmental conditions, social cohesion, technology, and human capital. The Global Power City Index (GPCI) [11] focuses mainly on how competitive and attractive cities are. The IMD Smart City Index [5] considers how residents perceive urban services and infrastructure. Other indices focus more on sustainability. These include the Arcadis Sustainable Cities Index [4], Corporate Knights Sustainable Cities Index [12], Sustainable Development Report (SDR) [13], and City Prosperity Index (CPI) [14]. They examine environmental, social, and economic outcomes of urban development.

Academics have also examined smart and sustainable city performance using different methods. Ozkaya and Erdin [15] used ANP to calculate the weights of indicators and TOPSIS to rank cities. Shmelev and Shmeleva [16] included economic, social, environmental, and smart city indicators in their assessment model. Abu-Rayash and Dincer [17] considered sustainability and smartness in a single framework. They also compared different weighting methods. Unal and Dursun [8] used RPEW and soft non-compensatory aggregation to score cities and they proposed a SSC index. The studies differ in the indicators they use and in how they normalize data, assign weights, and combine indicator values.

AHP is one of the methods used to evaluate urban sustainability and identify which SSC indicators are more important. Ameen and Mourshed [18] used this method in the Iraqi Urban Sustainability Assessment Framework. They assigned weights to indicators and ranked them based on local conditions and stakeholder priorities. Carli et al. [19] also used AHP, but their work focused on sustainable metropolitan cities. They looked at indicators related to energy, water, and environmental systems. Gazzeh [20] studied sustainable smart cities and used content analysis to identify indicators from previous studies. AHP was then used to rank these indicators according to their importance. Although the studies focused on different aspects of urban sustainability, they all used AHP to determine the relative importance of indicators.

ANP offers a related approach in which dependencies among assessment criteria can also be represented. Wey and Peng [21] integrated smart city and urban sustainability indicators into a common assessment framework and used ANP to account for dependencies among them. Their framework was illustrated through applications to Taipei and Singapore. DEMATEL and ANP approaches have been used by Ghaemi Rad et al. [22] for the criteria assessment in ubiquitous cities. These applications are relevant to SSC assessment because urban indicators may be connected across dimensions, and their relative importance may depend on how those connections are represented.

This study builds on the method used by Unal and Dursun [8]. It proposes a compact SSC assessment framework using 17 indicators selected from the literature review and reports published by different organizations. The data for these indicators come from publicly available sources, which are presented in the next section. RPEW, AHP, and ANP weighting methods are applied to the same cities and indicators to calculate indicator weights. The other steps, such as normalization and aggregation, are kept the same. The aim is to compare how different weighting methods affect SSC scores and city rankings.

3 Methodology

The SSC assessment starts with the selection of indicators, which are grouped into four dimensions. The data are then winsorized and normalized. Three different methods, RPEW, AHP, and ANP, are used to determine the indicator weights. Once the weights are obtained, the same aggregation and scoring procedures are used to calculate the SSC scores and rankings of the cities.

This allows the influence of the weighting method on the assessment results to be examined while keeping the remaining methodological steps consistent. The following subsections describe each stage of the framework.

3.1 SSC Index Structure and Indicator Selection

The SSC index includes 17 indicators. These indicators are divided into four dimensions. The dimensions are as follows: Environmental Sustainability, Smart Mobility and Infrastructure, Economic Performance, and Governance and Quality of Life. The indicators were chosen after reviewing existing smart city and sustainable city assessment frameworks. Their relevance to SSC performance and the availability of comparable data for the cities were considered during the selection process. Only indicators with publicly available data were included so that others could access the sources and reproduce the results [23–26].

The same indicators are used for three different weighting methods (AHP, ANP and RPEW). Table 1 (Appendix) lists the indicators and shows their dimensions, measurement units, and data sources. It also identifies whether each indicator is a benefit (B) or cost (C) criterion. For benefit criteria, higher values are better. For cost criteria, lower values are better.

3.2 Data Preprocessing and Normalization

A winsorization process is applied to limit the influence of extreme values. In this procedure, for each indicator j, lower and upper bounds are calculated. To evaluate this process, the $5th$ and $95th$ percentiles of its empirical distribution across all cities are used. The lower bound L_j and the upper bound U_j are calculated as follows:

$$L_j = Q_{0.05}(x_{\cdot j}), U_j = Q_{0.95}(x_{\cdot j}) \quad (1)$$

where $Q_{0.05}(x_{\cdot j})$ and $Q_{0.95}(x_{\cdot j})$ denote the 5th and 95th percentiles of indicator j calculated across all alternatives (cities in this case). The values that fall outside of the bounds are calculated as follows:

$$x'_{ij} = \begin{cases} L_j & \text{if } x_{ij} < L_j \\ x_{ij} & \text{if } L_j \le x_{ij} \le U_j \\ U_j & \text{if } x_{ij} > U_j \end{cases} \quad (2)$$

where x_{ij} represents the observed value of indicator j for city i, and x'_{ij} denotes the winsorized

value. The 5th and 95th percentile thresholds are applied to reduce the effect of extreme values. This step also helps not to remove too much information from the dataset. Next, the winsorized indicators are normalized using ranging from 0 to 1. Benefit (where higher values are preferred) and cost (where lower values are preferred) criteria are normalized using respectively the formulations (3) and (4):

$$n_{ij} = \frac{x'_{ij} - L_j}{U_j - L_j} \quad (3)$$

$$n_{ij} = \frac{U_j - x'_{ij}}{U_j - L_j} \quad (4)$$

where n_{ij} denotes the normalized value of indicator j for city i obtained after the winsorization and normalization procedures. As a result, all normalized indicator values are expressed on a common scale, where higher values represent better performance across all indicators. The same preprocessing and normalization procedures are used for the RPEW, AHP, and ANP applications, providing a common dataset for the subsequent weighting and scoring stages.

3.3 Weighting Methods

As mentioned in the previous sections, the main goal of this study is to compare city rankings which are calculated through three different weighting methods (RPEW, AHP, and ANP). RPEW calculates indicator weights combining entropy-based information with a penalty for redundancy between indicators. It means that if an indicator is correlated with another indicator (means that there is a redundancy), it gets lower value. Besides, this method is an objective method. AHP uses pairwise comparisons to calculate indicator weights within a hierarchical structure. ANP also uses pairwise comparisons, but it considers the relationships between dimensions and indicators through a network structure. The weights calculated by these methods are then applied to the same normalized data. The aggregation and scoring procedures are kept the same to compare how the different weights affect SSC scores and city rankings.

3.3.1 Redundancy Penalized Entropy Weighting (RPEW) Method

RPEW is used to derive objective indicator weights from the observed data [8]. The method combines entropy-based weighting with a correlation-based adjustment for redundancy. The entropy component reflects how much an indicator differentiates between cities, while the redundancy adjustment reduces the influence of information shared by correlated indicators.

First, a probability matrix is constructed based on the normalized indicator values. For each indicator j, the probability associated with city i is computed as:

$$p_{ij} = \frac{n_{ij}}{\sum_{i=1}^{m} n_{ij}} \quad (5)$$

where m shows the total number of cities. Next, the entropy value of each indicator j is then calculated as follows:

$$e_j = -\frac{1}{\ln(m)} \sum_{i=1}^{m} p_{ij} \ln(p_{ij}) \quad (6)$$

where $1/\ln(m)$ is a normalization constant ensuring that $0 \leq e_j \leq 1$. The logarithm of zero is undefined. In this study, if the probability values are 0 in the term $p_{ij} \ln(p_{ij})$ then it is treated as zero.

The degree of divergence is calculated as follows:

$$d_j = 1 - e_j \quad (7)$$

A correlation-based penalty factor is used to get lower redundancy between indicators. The Pearson correlation coefficient between indicators j and k denoted by ρ_{jk}. This coefficient is calculated using the normalized values of the indicator across all cities. The redundancy penalty is calculated as follows:

$$R_j = 1 - \frac{1}{K-1} \sum_{k \neq j} |\rho_{jk}| \quad (8)$$

where K is the total number of indicators. This formulation penalizes indicators that convey information already captured by others, regardless of correlation direction.

The final indicator weights are obtained by combining both components:

$$w_j^{RPEW} = \frac{d_j \cdot R_j}{\sum_j d_j \cdot R_j} \quad (9)$$

This procedure ensures that indicators with higher discriminatory power and lower redundancy receive greater importance.

3.3.2 Analytic Hierarchy Process (AHP)

AHP uses pairwise comparisons to calculate the relative weights of indicators within a hierarchical structure [9]. In this study, the hierarchy includes the main SSC assessment objective, four dimensions, and 17 indicators. The four dimensions are compared with each other. The indicators within each dimension are also compared. These comparisons use Saaty's 1–9 scale, where 1 means equal importance and 9 means extreme importance. Reciprocal values are used when the preference is reversed [9].

Each judgment set produces a comparison matrix $A^{(k)}$ whose entry ${a_{rs}}^{(k)}$ expresses the importance of element r relative to element s. Diagonal entries equal one, and opposite entries are reciprocals. For this study, pairwise judgments were collected from three domain experts, assigned equal importance, and combined using the geometric mean [27]:

$$\bar{a}_{rs} = \left(\prod_{k=1}^{K} {a_{rs}}^{(k)}\right)^{\frac{1}{K}} \quad (10)$$

where K = 3 and $\bar{a}_{rs}$ is an entry of the aggregated comparison matrix $\bar{A}$. The priority vector is obtained from its principal right eigenvector:

$$\bar{A}w = \lambda_{max} w \quad (11)$$

where λ_{max} is the largest eigenvalue and w is normalized to sum to one. The vector is computed iteratively by multiplying an initially uniform vector by $\bar{A}$ and normalizing the result until convergence.

Consistency is evaluated using the consistency index (CI) and consistency ratio (CR) [28]:

$$CI = \frac{\lambda_{max} - q}{q - 1} \quad ; \quad CR = \frac{CI}{RI_q} \quad (12)$$

where q is the matrix order and RI_q is the corresponding random index. RI values of 0.58, 0.90, and 1.12 are used for matrices of orders three, four, and five, respectively. A CR below 0.10 is adopted as the acceptable consistency threshold. This assessment applies to both individual and aggregated matrices; comparisons exceeding the threshold require review.

The dimension comparison matrix provides dimension weights α_d, while the within-dimension matrices provide local indicator weights $v_{j|d}$. The global weight of indicator j belonging to dimension d is calculated as:

$${w_j}^{AHP} = \alpha_d v_{j|d} \quad (13)$$

Dimension weights, local weights within each dimension, and global weights across all 17 indicators each sum to one. The resulting weights are applied to the same normalized dataset using the common aggregation and scoring procedure described in Section 3.4.

3.3.3 Analytic Network Process (ANP)

ANP incorporates interdependencies and feedback among criteria [10]. The 17 SSC indicators constitute four clusters corresponding to the index dimensions. A directed network identifies indicator-level influences. For each target indicator, linked indicators within each source cluster are compared using Saaty's 1–9 scale. Three equally weighted judgment sets which collected from the same three experts are aggregated by geometric mean; local priorities and consistency are determined as in Eqs. (10-12). These priorities form the unweighted supermatrix:

$$U = [u_{rs}]_{N \times N}, \quad N = 17 \quad (14)$$

Where r and s index source and target indicators, and u_{rs} is the corresponding local influence priority. If $r \to s$, then $u_{rs} = v_{r|s,a(r)}$, where $a(r)$ identifies the source cluster and $v_{r|s,a(r)}$ is the priority of r within that cluster for target s; otherwise, $u_{rs} = 0$. The function $b(s)$ identifies the cluster of targets s. Pairwise comparisons of source clusters with respect to target cluster b give $c_{a|b}$, the relative influence of source cluster a. The weighted supermatrix is constructed as:

$$w_{rs} = u_{rs} \frac{c_{a(r)|b(s)}}{\sum_{h \in \mathcal{A}_s} c_{h|b(s)}} \quad (15)$$

where, $W = [w_{rs}]_{N \times N}$ is the weighted supermatrix, $\mathcal{A}_s$ is the set of source clusters linked to target s, and h indexes these active clusters. Normalization over $\mathcal{A}_s$ makes every column of W sum to one. The limit supermatrix is obtained from successive powers of W:

$$L = \lim_{t \to \infty} W^t \quad (16)$$

where, t is the power index, and L is the limiting matrix when convergence occurs. Global ANP indicator weights are obtained from the row means of L:

$$w_j^{\mathrm{ANP}} = \frac{1}{N}\sum_{s=1}^{N} L_{js} \quad (17)$$

where, L_{js} is the element in row j and column s of the limit supermatrix; j indexes indicators, while s indexes its $N = 17$ columns. The global weights w_j^{ANP} sum to one across all indicators. The weight of dimension d is $w_d^{\mathrm{ANP}} = \sum_{j \in J_d} w_j^{\mathrm{ANP}}$, where J_d is its indicator set ($d = 1, \dots, 4$). Within each dimension, the normalized local weight of indicator $j \in J_d$ is $w_j^{\mathrm{ANP}} / w_d^{\mathrm{ANP}}$. These weights are used in the common aggregation and scoring procedure described in Section 3.4.

3.4 Aggregation and Scoring

To determine cities' dimension scores, indicator weights are multiplied with normalized values as follows:

$$S_i = \sum_j w_j \; n_{ij} \quad (18)$$

Then, the overall SSC score is calculated using geometric mean. The overall score for city i is defined as:

$$SSC_i = exp(\sum_{i=1}^{d} w_d ln(S_i + \varepsilon)) \quad (19)$$

where d is the number of dimensions, w_d denotes dimension weights, and ε is a small constant set to ε = 10^{-6} introduced to avoid numerical issues when dimension scores approach zero.

4 Case Study and Results

In this section city scores are calculated using the proposed framework. The same methodological steps are applied to raw data, and only weighting methods are changed. As mentioned, it the previous sections, proposed SSC assessment framework is applied to nine European cities using 2018 data. The analysis first compares the indicator weights obtained from each method. Next, SSC scores are calculated. Finally, Spearman's rank correlation coefficients and changes in city rankings are examined.

4.1 Comparison of Indicator Weights

The three methods assign different weights to the 17 SSC indicators. RPEW calculates weights based on the redundancy between indicators. On the other hand, AHP and ANP use expert judgments to determine the weights. AHP follows a hierarchical structure, while ANP considers relationships between indicators through a network structure. Table 2 shows the weights calculated using RPEW, AHP, and ANP.

Table 2. Comparison of Global Indicator Weights Obtained Using RPEW, AHP, ANP

Indicator	w_j^{RPEW}	w_j^{AHP}	w_j^{ANP}
PM2.5 Exposure	0.0499	0.1331	0.0229
Nighttime Urban Heat Island Intensity	0.0680	0.0507	0.0037
Green Area per Capita	0.0826	0.0601	0.0120
Share of Green Areas	0.0668	0.0366	0.0146
Tree Cover Share	0.1004	0.0767	0.0099
Public Transport Accessibility within a 10-Minute Walk	0.0586	0.0552	0.1579
Traffic Index	0.0488	0.0294	0.0964
People Killed in Road Accidents	0.0262	0.0978	0.0465
Fiber Access	0.0524	0.0171	0.0078
Broadband Access (30 Mbps+)	0.0259	0.0128	0.0157
GDP per Capita	0.0855	0.1333	0.1929
Labour Productivity	0.0467	0.0867	0.0826
Unemployment Rate	0.0535	0.0564	0.0846
Local Online Service Index	0.0394	0.0144	0.0055
Homicide Rate	0.0767	0.0507	0.0914
Quality of Life Index	0.0621	0.0599	0.1144
Property Price to Income Ratio	0.0566	0.0289	0.0412
Total	1.0000	1.0000	1.0000

Source: created by the authors.

Table 2 shows that the three methods assign different weights to some of the indicators. In RPEW, Tree Cover Share has the highest weight (0.1004). GDP per Capita (0.0855) and Green Area per Capita (0.0826) come next. For AHP, GDP per Capita (0.1333) and PM2.5 Exposure (0.1331) have the highest weights, followed by People Killed in Road Accidents (0.0978). The results are different for ANP. GDP per Capita has the highest weight (0.1929), followed by Public Transport Accessibility within a 10-Minute Walk (0.1579) and Quality of Life Index (0.1144).

These differences are particularly noticeable at the dimension level. Environmental Sustainability represents approximately 36.8% and 35.7% of the total weight under RPEW and AHP, respectively, but only 6.3% under ANP. In contrast, Economic Performance and Smart Mobility and Infrastructure account for approximately 36.0% and 32.4% of the total ANP weight, respectively. This suggests that the network-based evaluation places greater emphasis on economic and mobility-related indicators, whereas

environmental indicators receive relatively greater importance under RPEW and AHP.

Overall, the results demonstrate that applying different weighting approaches to the same indicator set can lead to substantially different assessments of indicator importance. However, these differences do not necessarily result in equivalent changes in city performance scores since their effects also depend on the normalized indicator values of each city. The implications of these weighting differences for overall SSC scores and rankings are examined in the following section.

4.2 Overall SSC Scores and Rankings

In this subsection the overall SSC scores of the nine European cities were calculated. As mentioned in the previous sections, all the calculation steps are kept the same except the weighting procedure. 3 different weighting methodologies are used. Although the same indicator and data set were used for all three approaches, differences in the assigned weights led to variations in the resulting city scores. Table 3 presents the overall SSC scores calculated with different weighting methods.

Table 3. Overall SSC Scores

City	SSC_i^{RPEW}	SSC_i^{AHP}	SSC_i^{ANP}
Stockholm	0.7204	0.7785	0.6306
Copenhagen	0.6969	0.6495	0.7356
Amsterdam	0.6367	0.6023	0.7806
Helsinki	0.6114	0.6702	0.5676
Berlin	0.5275	0.4531	0.4806
London	0.3997	0.4637	0.3981
Paris	0.3677	0.4116	0.5104
Budapest	0.3654	0.2808	0.3400
Rome	0.0080	0.0120	0.0041

Source: created by the authors.

The cities with the highest scores are not the same for all three weighting methods. Stockholm ranks first under RPEW (0.7204) and AHP (0.7785). However, Amsterdam has the highest score under ANP (0.7806). Copenhagen (0.7356) and Stockholm (0.6306) rank second and third, respectively. These cities generally perform well across the three methods, but their rankings change depending on the weights used. Rome and Budapest are at the lower end of the list in all three methods. Table 4 shows the city rankings based on their overall SSC scores.

Table 4. City Rankings under Different Weighting Methods

City	RPEW	AHP	ANP
Stockholm	1	1	3
Copenhagen	2	3	2
Amsterdam	3	4	1
Helsinki	4	2	4
Berlin	5	6	6
London	6	5	7
Paris	7	7	5
Budapest	8	8	8
Rome	9	9	9

Source: created by the authors.

As shown in Table 4, several cities got the same positions such as Budapest and Rome. However, the rest of the cities are affected by the choice of weighting method. Stockholm ranks first under RPEW and AHP. But under ANP it is the third best performing sustainable smart city. Stockholm changed its place with Amsterdam. Helsinki positioned to a higher place in AHP (From fourth to second). Paris also shows a better performance under ANP as Amsterdam. It improved from seventh under RPEW and AHP to fifth under ANP.

The results show that the weighting method can affect city rankings, especially when cities perform differently across the indicators. However, some cities remain in similar positions even when the indicator and dimension weights change. The next section compares the rankings in more detail using Spearman's rank correlation.

4.3 Rank Correlation and Ranking Stability Analysis

As discussed in 4.2, except for two cities (Rome and Budapest), the three weighting methods give different city rankings. Spearman's rank correlation coefficient was calculated for each pair of methods (RPEW-AHP, RPEW-ANP, AHP-ANP) to compare the obtained rankings. This coefficient shows how closely the city rankings are across the different weighting methods. The coefficient is calculated as follows:

$$\rho_s = 1 - \frac{6\sum_{i=1}^{n} d_i^2}{n(n^2-1)} \quad (20)$$

where ρ_s denotes Spearman's rank correlation coefficient. d_i represents the difference between the ranks assigned to city i by two weighting methods and n is the number of evaluated cities (n=9). Table 5 presents the Spearman Rank Correlations among weighting methods.

Table 5. Spearman Rank Correlations Among Weighting Methods

Weighting Methods	$\sum d_i^2$	ρ_s
RPEW – AHP	8	0.9333
RPEW – ANP	14	0.8833
AHP – ANP	26	0.7833

Source: created by the authors.

The Spearman rank correlations are positive and relatively high for all three pairs of methods. RPEW and AHP have the highest correlation, with a value of 0.9333. The correlation between RPEW and ANP is also high, at 0.8833. AHP and ANP have the lowest correlation, with a value of 0.7833. This shows that the rankings obtained from AHP and ANP have more differences compared to the other pairs. For example, Amsterdam ranks fourth with AHP, but its position changes to first with ANP. Stockholm ranks first with both RPEW and AHP. However, it drops to third place with ANP. Budapest remains in eighth place under all three methods. Similarly, Rome ranks ninth in all three methods. The results show that the rankings are generally similar, but some cities change positions depending on the weighting method used. These changes are more noticeable among the higher-ranked cities.

5 Discussion and Managerial Implications

The results of the case study show that the choice of weighting method is important in sustainable smart city assessment. RPEW, AHP, and ANP weighting methodologies were applied to the same indicators, and the same data were used. The normalization and aggregation procedures were also kept the same. However, city rankings changed. RPEW gave relatively more weight to environmental indicators. Environmental and economic indicators have relatively higher values in the AHP model. ANP gave higher weights to economic performance and smart mobility. This suggests that SSC results depend on how their weights are determined.

The differences due to different methodologies are also observed in the overall city rankings. Stockholm ranked first when RPEW and AHP models are used. Amsterdam achieved the highest score under ANP. Spearman Rank Correlations are calculated to compare the rankings of each couple of weighting methodology. Despite the differences in rankings, the Spearman correlation coefficients, ranging from 0.7833 to 0.9333, indicate a relatively high level of agreement among the three methods. While the positions of some leading cities changed, Budapest and Rome remained at the bottom of the rankings in all three approaches. These findings suggest that some ranking positions are more sensitive to weighting choices than others. That is why, using only one weighting method may not give a complete picture of how cities compare in terms of SSC performance.

The results may also be useful for policymakers, urban planners, and city administrators. The proposed index shows how cities perform in environmental, mobility, economic, and governance-related areas. City administrators can use these results together with local priorities and development goals instead of relying only on overall rankings. The index uses a limited number of indicators, and the data are available from public sources. This makes it easier to apply the same approach to other cities and future studies.

6 Conclusions and Future Research

This study proposes a compact Sustainable Smart City index consisting of 17 indicators and four dimensions. The dimensions are as follows: Environmental Sustainability, Smart Mobility and Infrastructure, Economic Performance, and Governance and Quality of Life. The case study is applied using three different weighting approaches to nine European cities using 2018 data. To examine how different weighting methods influence SSC performance, only weighting methodologies changed and the rest of the procedures kept the same. This allowed the effects of alternative weighting approaches on city scores and rankings.

The three methods gave different indicator weights and city rankings. Stockholm ranked first with RPEW and AHP, while Amsterdam came first with ANP. However, the Spearman rank correlations were relatively high, showing that the overall rankings were generally similar across the three methods. This means that the weighting method can affect SSC results, even when the same indicators and scoring procedures are used. The proposed framework uses a relatively small set of indicators and compares an objective weighting method with methods based on expert judgments. It also provides a clear procedure that other researchers can follow and reproduce when assessing sustainable smart city performance.

This study also has certain limitations. The case study is only applied to nine European cities, and a single reference year is used. In addition, AHP and ANP rely on pairwise judgments. Future studies could include more cities and additional indicators if

reliable data are available. Using data from several years would also make it possible to examine how SSC performance changes over time. Further studies could examine whether the results change with different expert judgments or different number of experts. This could help explain how methodological choices affect SSC assessment results.

Acknowledgement:
The authors gratefully acknowledge the financial support provided by the TUBITAK-BIDEB 2211 National PhD Scholarship Program.

Declaration of Generative AI and AI-assisted Technologies in the Writing Process

During the preparation of this work, the author(s) utilized artificial intelligence (AI) technologies solely for the purpose of linguistic refinement and grammatical correction. Following the application of these tools, the author(s) comprehensively reviewed, verified, and edited the resulting text. The author(s) maintain full accountability and responsibility for the accuracy, integrity, and final content of the publication.

References:

[1] A. M. Toli and N. Murtagh, "The Concept of Sustainability in Smart City Definitions," Frontiers in Built Environment, vol. 6, no. 77, 2020. https://doi.org/10.3389/fbuil.2020.00077.

[2] H. Ahvenniemi, A. Huovila, I. Pinto-Seppä and M. Airaksinen, "What Are the Differences between Sustainable and Smart Cities?," Cities, vol. 60, pp. 234–245, 2017. https://doi.org/10.1016/j.cities.2016.09.009.

[3] S. E. Bibri and J. Krogstie, "Smart Sustainable Cities of the Future: An Extensive Interdisciplinary Literature Review," Sustainable Cities and Society, vol. 31, pp. 183–212, 2017. https://doi.org/10.1016/j.scs.2017.02.016.

[4] Arcadis, The Arcadis Sustainable Cities Index 2024. Amsterdam, The Netherlands, 2024. Available: https://www.arcadis.com/en/insights/perspectives/global/sustainable-cities-index-2024.

[5] IMD World Competitiveness Center, IMD Smart City Index 2025. Lausanne, Switzerland, 2025. Available: https://imd.widen.net/s/psdrsvpbk7/imd_smart_city_2025_report. Accessed: May 30, 2026.

[6] IESE Business School, University of Navarra, Cities in Motion Index 2024. Pamplona, Spain, 2024.Available: https://www.iese.edu/media/research/pdfs/ST-0649-E.pdf. Accessed: May 30, 2026.

[7] United Nations Human Settlements Programme (UN-Habitat), World Cities Report 2024: Cities and Climate Action. Nairobi, Kenya: UN-Habitat, 2024. ISBN: 978-92-1-132955-1. Available: https://unhabitat.org/wcr/. Accessed: May 30, 2026.

[8] M. Unal and M. Dursun, "Developing a Composite Sustainable Smart City Performance Assessment Index: A Novel Indexing Model and Cross-Country Application," Systems, vol. 14, no. 3, p. 330, 2026. https://doi.org/10.3390/systems14030330.

[9] T. L. Saaty, "Decision Making with the Analytic Hierarchy Process," International Journal of Services Sciences, vol. 1, no. 1, pp. 83–98, 2008. https://doi.org/10.1504/IJSSCI.2008.017590.

[10] T. L. Saaty, "Fundamentals of the Analytic Network Process—Dependence and Feedback in Decision-Making with a Single Network," Journal of Systems Science and Systems Engineering, vol. 13, pp. 129–157, 2004. https://doi.org/10.1007/s11518-006-0158-y.

[11] Mori Memorial Foundation, Global Power City Index 2025 Summary. Tokyo, Japan, 2025. Available: https://mori-m-foundation.or.jp/english/ius2/gpci2/index.shtml Accessed: May 30, 2026.

[12] Corporate Knights, The Sustainable Cities Index 2023. Toronto, ON, Canada, 2023. Available: https://www.corporateknights.com/wp-content/uploads/2023/04/2023-Sustainable-Cities-Index-Report-1.pdf. Accessed: May 30, 2026.

[13] J. D. Sachs, G. Lafortune and G. Fuller, Sustainable Development Report 2024. Paris, France: Sustainable Development Solutions Network, 2024. Available: https://s3.amazonaws.com/sustainabledevelopment.report/2024/sustainable-development-report-2024.pdf. Accessed: May 30, 2026.

[14] United Nations Human Settlements Programme (UN-Habitat), City Prosperity Index. Available:

https://data.unhabitat.org/pages/city-prosperity-index. Accessed: May 30, 2026.

[15] G. Ozkaya and C. Erdin, "Evaluation of Smart and Sustainable Cities through a Hybrid MCDM Approach Based on ANP and TOPSIS Technique," Heliyon, vol. 6, Art. no. e05052, 2020. https://doi.org/10.1016/j.heliyon.2020.e05052

[16] S. E. Shmelev and I. A. Shmeleva, "Global Urban Sustainability Assessment: A Multidimensional Approach," Sustainable Development, vol. 26, no. 6, pp. 904–920, 2018. https://doi.org/10.1002/sd.1887.

[17] A. Abu-Rayash and I. Dincer, "Development of an Integrated Model for Environmentally and Economically Sustainable and Smart Cities," Sustainable Energy Technologies and Assessments, vol. 73, Art. no. 104096, 2025. https://doi.org/10.1016/j.seta.2024.104096.

[18] R. F. M. Ameen and M. Mourshed, "Urban Sustainability Assessment Framework Development: The Ranking and Weighting of Sustainability Indicators Using Analytic Hierarchy Process," Sustainable Cities and Society, vol. 44, pp. 356–366, 2019. https://doi.org/10.1016/j.scs.2018.10.020.

[19] R. Carli, M. Dotoli and R. Pellegrino, "Multi-Criteria Decision-Making for Sustainable Metropolitan Cities Assessment," Journal of Environmental Management, vol. 226, pp. 46–61, 2018. https://doi.org/10.1016/j.jenvman.2018.07.075.

[20] K. Gazzeh, "Ranking Sustainable Smart City Indicators Using Combined Content Analysis and Analytic Hierarchy Process Techniques," Smart Cities, vol. 6, no. 5, pp. 2883–2909, 2023. https://doi.org/10.3390/smartcities6050129.

[21] W.-M. Wey and T.-C. Peng, "Study on Building a Smart Sustainable City Assessment Framework Using Big Data and Analytic Network Process," Journal of Urban Planning and Development, vol. 147, no. 3, Art. no. 04021031, 2021. https://doi.org/10.1061/(ASCE)UP.1943-5444.0000704.

[22] T. Ghaemi Rad, A. Sadeghi-Niaraki, A. Abbasi and S.-M. Choi, "A Methodological Framework for Assessment of Ubiquitous Cities Using ANP and DEMATEL Methods," Sustainable Cities and Society, vol. 37, pp. 608–618, 2018. https://doi.org/10.1016/j.scs.2017.11.024.

[23] OECD, OECD Data Explorer. Available: https://data-explorer.oecd.org/. Accessed: May 30, 2026.

[24] Numbeo, Numbeo Database. Available: https://www.numbeo.com/. Accessed: May 30, 2026.

[25] Eurostat, Cities and Greater Cities Database. Available: https://ec.europa.eu/eurostat/web/cities. Accessed: May 30, 2026.

[26] United Nations Department of Economic and Social Affairs (UN DESA), United Nations E-Government Survey 2018: Gearing E-Government to Support Transformation towards Sustainable and Resilient Societies. New York, NY, USA: United Nations, 2018. Available: https://publicadministration.un.org/egovkb/Portals/egovkb/Documents/un/2018-Survey/E-Government%20Survey%202018_FINAL%20for%20web.pdf. Accessed: May 30, 2026.

[27] E. Forman and K. Peniwati, "Aggregating Individual Judgments and Priorities with the Analytic Hierarchy Process," European Journal of Operational Research, vol. 108, no. 1, pp. 165–169, 1998. https://doi.org/10.1016/S0377-2217(97)00244-0

[28] A. Ishizaka and A. Labib, "Review of the Main Developments in the Analytic Hierarchy Process," Expert Systems with Applications, vol. 38, no. 11, pp. 14336–14345, 2011. https://doi.org/10.1016/j.eswa.2011.04.143

Contribution of Individual Authors to the Creation of a Scientific Article (Ghostwriting Policy)

The authors equally contributed in the present research, at all stages from the formulation of the problem to the final findings and solution.

Sources of Funding for Research Presented in a Scientific Article or Scientific Article Itself

This research is financially supported by Galatasaray University Research Fund Grant Number FBA-2026-1335.

Conflict of Interest

The authors have no conflicts of interest to declare that are relevant to the content of this article.

Creative Commons Attribution License 4.0 (Attribution 4.0 International, CC BY 4.0)

This article is published under the terms of the Creative Commons Attribution License 4.0
https://creativecommons.org/licenses/by/4.0/deed.en_US

APPENDIX

Table 1. Indicators Included in the Proposed SSC Assessment Framework

Dimension	Indicator	Unit	Type	Source
Environmental Sustainability	PM2.5 Exposure	μg/m³	C	OECD [23]
Environmental Sustainability	Nighttime Urban Heat Island Intensity	°C	C	OECD [23]
Environmental Sustainability	Green Area per Capita	m²/person	B	OECD [23]
Environmental Sustainability	Share of Green Areas	%	B	OECD [23]
Environmental Sustainability	Tree Cover Share	%	B	OECD [23]
Smart Mobility & Infrastructure	Public Transport Accessibility within a 10-Minute Walk	%	B	OECD [23]
Smart Mobility & Infrastructure	Traffic Index	Index Score	C	Numbeo [24]
Smart Mobility & Infrastructure	People Killed in Road Accidents	per 10,000 population	C	Eurostat [25]
Smart Mobility & Infrastructure	Fiber Access	% of households	B	OECD [23]
Smart Mobility & Infrastructure	Broadband Access (30 Mbps+)	% of households	B	OECD [23]
Economic Performance	GDP per Capita	USD (PPP)	B	OECD [23]
Economic Performance	Labour Productivity	GDP per employed person	B	OECD [23]
Economic Performance	Unemployment Rate	%	C	OECD [23]
Governance & Quality of Life	Local Online Service Index	Score	B	UN E-Government Survey 2024 [26]
Governance & Quality of Life	Homicide Rate	per 100,000 population	C	OECD [23]
Governance & Quality of Life	Quality of Life Index	Index Score	B	Numbeo [24]
Governance & Quality of Life	Property Price to Income Ratio	Ratio	C	Numbeo [24]

Source: created by the authors.