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Using Multi-Criteria Decision-Making for Smart City Evaluation and Ranking

Akıllı Şehirleri Çok Kriterli Karar Verme ile Değerlendirme ve Sıralama

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ÖZ

Kentsel alanların büyümesi ve gelişimiyle birlikte akıllı şehirlerin evrimi, kentsel planlama ve sürdürülebilirlik için kritik bir öneme sahip olmuştur. Şehirler, vatandaşların yaşam kalitesini artırma ve kentsel işlevlere yanıt verme amacıyla ekonomik büyümeyi teşvik etmek için akıllı olma zorunluluğu ile karşı karşıyadır. Bu bağlamda, şehirler genellikle performansı ve verimliliği artırmak için veriye dayalı akıllı teknolojilere yatırım yapmaktadırlar. Ancak bir şehri akıllı olarak değerlendirebilmek için, sadece teknoloji alanında değil, çeşitli boyutlardaki kriterleri karşıladığını göstermek gerekmektedir. Bunu yapmanın en etkili yollarından biri, şehrin rakipleri arasında nasıl bir konuma sahip olduğunu analiz etmektir. Bu makale, esas alınan veri tabanlarında ortak olan dünya genelinde 48 şehrin akıllı şehrin yeterliliğini, başlıca Technique for Order Performance by Similarity to Ideal Solution (TOPSIS) ve entropi ağırlık yöntemlerinden oluşan bir metodoloji kullanarak incelemektedir. Önerilen metodoloji, şehirleri yedi farklı boyutta nesnel şekilde analiz etmektedir. Elde edilen sonuçlar, şehirlerin akıllı şehir olmadaki genel performanslarının yanı sıra, yatırım yaparak güçlendirilmesi gereken zayıf yönlerini de ortaya koymaktadır. Bu yaklaşım, şehir plancılarına, politika yapıcılara ve diğer paydaşlara, sürdürülebilir akıllı şehirlerin gelişiminde en iyi stratejileri belirleyebilmelerine, ilerlemeyi takip edebilmeleri ve yatırımları etkin bir şekilde yönlendirebilmeleri için değerli bir araç sunmaktadır.

Anahtar Kelimeler: Akıllı Şehir, Dijital Altyapı, Çok Kriterli Karar Verme, TOPSIS, Entropi

ABSTRACT

With the growth and development of urban areas, the evolution of smart cities has become critically important for urban planning and sustainability. Cities are faced with the imperative to be 'smart' to enhance the quality of life for their citizens, respond to urban functions, and promote economic growth. In this context, cities frequently invest in data-driven smart technologies to boost performance and efficiency. However, to deem a city 'smart', it is essential to demonstrate that it meets criteria not only in the technology sector but across various dimensions. One of the most effective ways to do this is to analyze a city's standing amongst its competitors. This paper examines the smart city proficiency of 48 cities worldwide that are common in the referenced databases, using a methodology primarily composed of the TOPSIS and entropy weight methods. The proposed methodology objectively evaluates cities across seven different dimensions. The results highlight not only the general performance of cities in becoming smart but also pinpoint the areas that require strengthening through investments. This approach offers city planners, policymakers, and other stakeholders a valuable tool to identify best practices, monitor progress, and efficiently direct investments in the evolution of sustainable smart cities.

Keywords: Smart City, Digital Infrastructure, Multi-Criteria Decision-Making, TOPSIS, Entropy

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INTRODUCTION:

A smart city is an urban area that employs advanced technology, data analytics, and intelligent systems to manage diverse facets of city life, such as transportation, energy, waste management, and public services. The paramount objective of smart cities is to improve the quality of life for residents, streamline resource utilization, and mitigate the environmental consequences of urbanization (Pandiyan et al., 2023). The term "smartness" typically characterizes a city's capability to foster well-being for its inhabitants (Cai et al., 2023).

This paper endeavors to examine the standing of various cities, with a particular focus on Istanbul, among 48 globally dispersed cities assessed through the Global Power City Index (GPCI) (GPCI 2022). These cities were the common cities in GPCI and in OECD databases. While multi-criteria decision-making methods (MCDM) have recently been employed in smart city evaluations, this study is pioneering in its combination of dimensions and indicators derived from two distinct perspectives: European and Japanese. The conceptualization and execution of the smart city idea are influenced by cultural, economic, and spatial contexts (Vanlı and Akan, 2023). European cities, enriched by lengthy histories, often grapple with challenges tied to infusing modern technologies into age-old infrastructure, all while safeguarding cultural legacies. Conversely, Japanese cities tend to seamlessly incorporate high-tech solutions into their urban landscapes (Barett et al., 2021) (Okubo et al., 2022). Nonetheless, spatial limitations are a shared concern for both. Japan, with its compact urban centers, susceptibility to natural calamities, and dwindling rural populace, necessitates resilient and ultra-efficient urban strategies. Conversely, the European smart city paradigm predominantly centers on minimizing carbon emissions, championing energy-efficient architectures, and promoting public transit. From a European viewpoint, smart cities frequently accentuate public involvement, ensuring that technological solutions resonate with the demands of all residents, encompassing those from marginalized sectors. In contrast, Japan adopts a top-down methodology, where tech conglomerates and governmental entities hold pivotal roles in smart city initiatives. European Union grants and endorsements give precedence to projects boasting broad relevance across its member nations. In Japan, the private sector, epitomized by tech behemoths like Panasonic, Toyota, and Hitachi, has a pronounced presence. Europe, with its tapestry of cultures, dialects, and histories, underscores multiculturalism in its smart cities. This commitment ensures that the distinctive essence of each city is factored into its evolution towards *smartness*.

The proposed assessment methodology commences by identifying the appropriate performance criteria or indicators for gauging a city’s smartness (Spicer et al., 2023). Seven main dimensions as suggested by Organization for Economic Cooperation and Development (OECD) (OECD 2022) are adopted. These are integrated with the smart city indicators proposed by Mori Institute (GPCI 2022). These indicators mirror a city’s assimilation of technology and the utilization of data-driven strategies to augment the urban living experience.

Givent that the data sources omit the weights of the indicators/criteria, it’s imperative to ascertain the priority weights of each criterion. Instead of using the Analytic Hierarchy Process (AHP) or Analytic Network Process (ANP) – methodologies frequently cited in related literature – this study employs the entropy method to determine the weights. This choice is motivated by the entropy method's ability to omit subjective judgments or expert opinions. The evaluation of the 48 cities under scrutiny is conducted via the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) methodology. This method is favored because it is a comprehensive approach that is commonly applied to measure the relative performances of various alternatives in a simple mathematical form. It provides a ranking of alternatives based on their relative closeness to the ideal solution. Moreover, TOPSIS is versatile enough to process both quantitative and qualitative data, seamlessly merging with other MCDM techniques or weighting systems to bolster the overarching decision-making trajectory. Within this paper, cities' performance metrics are sourced from the GPCI.

The empirical application elucidates both a holistic ranking and a categorical ranking within each city dimension. Such results spotlight any inadequacies cities may face on their digital transformation journey, pinpointing potential avenues for enhancement.

As time has passed, it has become essential for all governments to enhance various aspects of urban areas. Observing the tangible benefits of intelligent transportation modalities, eco-friendly sustainable environments, and enhanced citizen well-being has intensified global cognizance. This transformation is perceived less as an opulence and more as a quintessential necessity. It's envisaged that the assessment methodology introduced in this work will simplify resource allocation challenges, especially pertinent to cities in developing nations.

The rest of the paper is organized as follows. Section 2 enumerates various related literature. A succinct theoretical foundation of the methods invoked during the numerical application is presented in Section 3. Section 4 systematically details the evaluation process's outcomes, and Section 5 concludes the paper by examining these findings and proposing potential future works.

1. Related Works in Literature

The notion of smart cities has its roots in the broader and older discourse of urban planning and development, where technology and data have been leveraged to enhance urban living. However, the formal conceptualization of the term and its pervasive use in contemporary literature can be traced back to the early 1990s. Nowadays, both international and national academic literature include a considerable number of studies that concentrate on the indicators of smartness and the evaluation of the cities concerning different dimensions of smartness. Cities are complex systems with many interwined variables, hence the literature for ranking smart cities have started to use MCDM techniques in 2017 (Dall'O et al., 2017). The authors have used MCDM because it offers a systematic approach to handle these multiple perspectives simultaneously. In that paper, the authors proposed their own MCDM approach to evaluate the smartness of three municipalities in Northern Italy. In 2018, two studies ranked cities primarily using online surveys or questionnaires. Aihemaiti and Zaim (2018) ranked 40 randomly selected Turkish cities, with Balıkesir at the top, and İstanbul positioned 25th.

In Table 1, the most related literature is chosen and presented giving their main objective, used methods, and chosen indicators for realizing the aim. The terms 'indicators' and 'criteria' are used interchangeably throughout the paper. Furthermore, Table 1 introduces the dataset to which the authors apply their proposed methodologies.

Various works have taken six dimensions (people, living, mobility, economy, environment, and governance), that are considered as Smart City Wheel (Aihemaiti and Zaim 2018), and they are said to be suitable for ISO 37120 standard (Dall'O et al., 2017). In our work, the proposed seven evaluation criteria also encapsulate these six dimensions. The study by Özkaya and Erdin (2020) is the most similar compared to our paper. The authors aim to rank smart cities using the ANP and TOPSIS methods. They selected 44 cities from the Global Power City Index (GPCI) to evaluation. However, in contrast to our work, they exclusively used the GPCI indicators. They ranked Tokyo at the top, followed by London and New York respectively in the overall ranking. Then in 2021 and 2022, the cities in Finland (Ahvenniemi and Huovilla, 2021), Poland (Hajduk, 2021), İran (Mokarrari and Torabi, 2021) and China (Fang and Chan, 2022) have been ranked by using content analysis, TOPSİS, different multi- attribute decision making approaches and clustering, respectively. Hadjuk (2021) used TOPSIS to rank 66 Polish cities that align with the smart city concept. The data for this study was sourced from the Local Data Bank Polish

Central Statistical Office. Notably, the author determined the weight coefficients for indicators based on expert opinions. This approach could lead to potential subjectivity in weighting, which differs from our method. In another similar study, Adali et al. (2022) introduced a grey extension of an integrated Level Based Weight Assessment & Evaluation Based on Distance from average Solution. The authors utilized GPCI for generating both criteria and city statistics. While the GPCI has sub-criteria beneath its main criteria, unlike our research, Adali et al. did not consider the weights and values of these sub-criteria.

Table 1. Related works in literature

Primary work	Aim	Methods	Dataset	Criteria / Indicators
Dall'O et al. (2017)	Evaluate the smartness of a city	Their proposed methodology	3 municipalities in Northern Italy	People, living, mobility, economy, environment, governance (ISO 37120 standard)
Aihemaiti and Zaim (2018)	Rank smart cities	Online survey, Z-transformation method	Virtual dataset for randomly selected 40 cities	Smart City Wheel: People, living, mobility, economy, environment, governance
Garau and Pavan (2018)	Evaluate and measure the quality of urban life	Analysis using checklists, questionnaires, and thematic maps	The city of Cagliari	Use and fruitation, health and well-being, appearance, management, environment, safety, and security
Özkaya ve Erdin (2020)	Rank smart cities	ANP, TOPSIS	44 cities in GPCI	People, living, mobility, economy, environment, governance
Ahvenniemi and Huovila (2021)	Examine how smartness and sustainability are presented	Content analysis	6 largest Finnish cities	ICT and technology, human and social capital development, entrepreneurship promotion and innovativeness, cooperative approach and citizen engagement, internationality, and economic growth
Hajduk (2021)	Rank smart cities	TOPSIS	66 Polish cities	Economy, environment, transportation, social capital, quality of life, management
Koca et al. (2021)	Evaluate the relationships between indicators and sub-indicators	DEMATEL	Data obtained from questionnaires of 10 experts	People, living, mobility, economy, environment, governance
Mokarrari and Torabi (2021)	Rank smart cities	6 MADM methods	5 most important cities in İran	People, living, mobility, economy, environment, governance
Fang and Shan (2022)	Classify cities in terms of the infrastructure readiness level	Principal component analysis, K-means clustering	275 Chinese cities	ISO – Sustainable Cities and Communities Standard – Indicators for Smart Cities
Yaşar et al. (2022)	Evaluate a selected city in terms of smart city applications	ANP, PROMETHEE	Districts of Ankara	People, living, mobility, economy, environment, governance
Adali et al. (2022)	Measure the smartness level of cities	Extension of LBWA & EDAS	17 cities among the cities in GPCI	Economy, R&D, cultural interaction, livability, environment, accessibility
Our paper	Evaluate the smartness of a city and rank them	Entropy, TOPSIS	48 cities in GPCI	The combination of the OECD The Going Digital Toolkit and the GPCI

Numerous studies employ MCDM techniques to evaluate or rank cities. This is largely because cities have multiple criteria for assessment, and these criteria a city, and they have relationships among them. Additionally, as demonstrated by the two data sources in this paper, publicly available numerical evaluations are accessible. Thus, MCDM methods emerge as one of the most fitting methodologies for such evaluations.

As Turkey is a member of the OECD and there are a considerable number of smart cities in Europe, we believe that considering its goals would be a more appropriate assessment, especially for evaluating the smartness of Turkish cities among others. Hence, in this paper, the indicators of GPCI are matched to the policies of the OECD. Another difference is the chosen method for determining the weights of the criteria. In our work, the entropy method is used instead of ANP, because of its objectiveness, leaving out all subjective expert opinions. The objective performance values are taken from the most recent GPCI report.

2. Evaluation Methodology

2.1. Evaluation Criteria, Sub-criteria, and Data

In this sub-section, the approach while determining the evaluation criteria/indicators, sub-criteria, and performance scores will be introduced in detail.

As the first step, determining the evaluation criteria, two data sources are associated: OECD, a global policy forum (OECD 2022), and Mori Memorial Foundation, a private research institute. OECD published 'The Going Digital Toolkit[2]', which is a user-friendly checklist for guiding countries to evaluate the level of their digital development efforts and then propose policies. It enables the authorities to examine whether a country can use digital technologies to create new or improved business processes, cultural activities, customer experiences, or communications infrastructures. This toolkit is built with respect to the Going Digital Integrated Policy Framework, with seven policy dimensions that need to be coordinated (OECD 2022):

Access to data-driven and digital innovation, good jobs for all, social prosperity and inclusion, trust in the digital age, and market openness in digital business environments. These seven dimensions are taken as the main criteria of the proposed methodology (Table 2). The toolkit computes the level of digital development of the selected countries according to the indicators determined by OECD. In this paper, the objective is to combine the data offered by two geographically different sources. Therefore, as the second step of our methodology, while determining the sub- criteria, a subset of the indicators of the Global Power City Index (GPCI 2022) are taken. GPCI has being publishing annually since 2008 by the Mori Memorial Foundation Institute for Urban Strategies, which is a Japanese private research institute that studies urban renewal and development fields to create ideal urban environments.

The index evaluates and ranks the major cities of the world according to their comprehensive power to attract people, capital, and enterprises from around the world. They consider six main dimensions (Economy, Research and Development, Cultural Interaction, Livability, Environment, and Accessibility), with each its own indicators. Hence, in this paper, the indicators provided by GPCI are matched to the policies of OECD. The (+) and (-) signs specified after each sub- criterion in Table 2 represent whether this sub-criterion is a benefit or cost criterion, respectively. Enabling access to communications infrastructures, services, and data (C_1) considers both ease of accessing them and their sustainability. The ICT readiness of the citizens (C_{11}), renewable energy (C_{12}) and waste recycling rate (C_{13}), and CO_2 emissions per capita (C_{14}) are taken. These indicators are believed to be among the indicators to assess sustainability. Moreover, the international network of the city is included in this category since this may show the accessibility of the city to foreign services or opportunities. The indicators of the number of cities with direct international flights (C_{15}) and international freight flows (C_{16}) are chosen to reflect the international network of the city.

Table 2. Criteria and sub-criteria

Access to communications infrastructures, services, and data (C_1)
ICT readiness (C_{11}) (+)
Renewable energy rate (C_{12}) (+)
Waste recycle rate (C_{13}) (+)
CO_2 emissions per capita (C_{14}) (-)
Cities with direct international flights (C_{15}) (+)
International freight flows (C_{16}) (+)
Effective use of digital technologies and data (C_2)
World's Top 500 companies (C_{21}) (+)
Air quality (C_{22}) (+)
Water quality (C_{23}) (+)
Data-driven and digital innovation (C_3)
Number of researchers (C_{31}) (+)
World's top universities (C_{32}) (+)
R&D expenditure (C_{33}) (+)
Number of patents (C_{34}) (+)
Number of startups (C_{35}) (+)
Good jobs for all (C_4)
Total employment (C_{41}) (+)
Wage level (C_{42}) (+)
Availability of skilled human resources (C_{43}) (+)
Variety of workplace options (C_{44}) (+)
Total unemployment rate (C_{45}) (-)
Social prosperity and inclusion (C_5)
Workstyle flexibility (C_{51}) (+)
Housing rent (C_{52}) (-)
Price level (C_{53}) (-)
Social freedom and equality (C_{54}) (+)
Nominal GDP (C_{55}) (+)
Cultural content export value (C_{56}) (+)
Number of foreign residents (C_{57}) (+)
Urban greenery (C_{58}) (+)
Public transportation use (C_{59}) (+)
Commuting time (C_{510}) (-)
Traffic congestion (C_{511}) (-)
Trust in the digital age (C_6)
Political, economic, and business risk (C_{61}) (-)
Market openness in digital business environments (C_7)
GDP growth rate (C_{71}) (+)
Economic freedom (C_{72}) (+)
Stock market capitalization (C_{73}) (+)

In order to evaluate how a city effectively uses digital technologies and data (C_2), the indicators of air (C_{22}) and water quality (C_{23}) are chosen, as they are the consequences of how well the data technologies are used to create a comfortable environment. Furthermore, the number of the world's top 500 companies (C_{21}) is included since most of them are IT companies and their existence shows that the current digital competition has been reached.

The research and development (R&D) efforts are considered in data-driven and digital innovation criteria (C_3). The number of researchers (C_{31}), world's top universities (C_{32}), R&D expenditure (C_{33}), number of patents (C_{34}), and startups (C_{35}) indicators are chosen in this group. They reflect the city's state of academic resources and its research environment.

Providing good jobs for all citizens (C_4) is one of the key solutions to most of the various citizens' issues. As an indicator of human capital, total employment (C_{41}) is chosen. Wage level (C_{42}), availability of skilled human resources (C_{43}), and variety of workplace options (C_{44}) are taken to assess the business environment. Then, the total unemployment rate (C_{45}) is selected to consider the city's working environment.

Social prosperity is defined as a well-being approach that measures the quality of life at the local level, whereas social inclusion defines the process of how individuals and groups take part in society. Therefore, various indicators from different dimensions have been chosen. The nominal gross domestic product (C_{55}) is chosen to reflect the market size that an individual faces. The number of foreign residents (C_{57}) is taken to show the international interaction of the city. The cultural content export value (C_{56}) is selected to reflect the city's trendsetting potential. The cost of living is reflected in the price level (C_{53}) and housing rent (C_{52}) indicators. The level of social freedom and equality (C_{54}) is taken for considering the citizen's well-being. Urban greenery (C_{58}), workstyle flexibility (C_{51}), public transportation use (C_{59}), commuting time (C_{510}), and the level of traffic congestion (C_{511}) are chosen to reflect the urban, and environment and comfortability of the city.

Trust in the digital age (C_6) is considered by the political, economic, and business risk indicator of the city (C_{61}), which is further related to the ease of doing business. Finally, economic freedom (C_{72}), stock market capitalization (C_{73}), and GDP growth rate (C_{71}) are chosen to evaluate economic vitality, market attractiveness, and therefore market openness in digital business environments (C_7).

At the end of the examination phase, when the findings of the research are turned into account, the fundamental criteria when evaluating the smartness of a city are decided to be gathered into seven main criteria and related sub-criteria as introduced in Table 2.

2.2. Methodologies

In this section, two main methods (entropy weight method and TOPSIS) of the proposed numerical methodology will be introduced.

2.2.1. The entropy weight method

In information theory, entropy is determined as the measurement of the degree of randomness or the increase in the disorganization within a system (Shannon 1948). A low entropy value corresponds to a low level of disorder within the system. The entropy weight method is based on the amount of information to determine the criteria weight. In this work, the entropy weight method is applied to determine the weight of the criteria and sub-criteria (a.k.a. indicators), which is calculated as following steps:

Step 1: The proportion P_{ij} is calculated for each indicator (1):

$$P_{ij} = X_{ij} \,/\, \sum X_{ij} \tag{1}$$

where X_{ij} is the value of the indicator *i* for spatial position *j*.

Step 2: The information entropy value e_i of each indicator *i* is calculated with (2):

$$e_i = -\left(\frac{1}{\ln(m)}\right) \sum P_{ij} \ln\left(P_{ij}\right) \tag{2}$$

where *m* is the total number of the i^{th} indicator.

Step 3: The differential coefficient of i^{th} indicator g_i is computed (3). Since the coefficient has a negative correlation with the entropy value, the equation is defined as:

$$g_i = 1 - e_i \tag{3}$$

Step 4: The weights w_i for each indicator *i* is calculated as:

$$w_i = \frac{g_i}{\sum g_i} \tag{4}$$

2.2.2. Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS)

TOPSIS method, first introduced in 1981, selects the optimal alternative based on its proximity to the ideal solution, and its farthest distance from the negative-ideal solution (Hwang and Yoon 1981). The ideal solution aims to maximize benefits while minimizing overall costs. In contrast, the negative-ideal solution seeks to minimize benefits and simultaneously maximize total costs (Büyüközkan and Işıklar 2007).

The decision matrix *D* with alternatives and criteria is:

$$D = \begin{array}{c c} & \begin{array}{ccc} C_1 & \dots & C_n \end{array} \\ \begin{array}{c} A_1 \\ \dots \\ A_m \end{array} & \begin{pmatrix} X_{11} & \cdots & X_{1n} \\ \vdots & \ddots & \vdots \\ X_{m1} & \cdots & X_{mn} \end{pmatrix} \end{array} \tag{5}$$

where $A_1, A_2, \dots, A_m$ are alternatives, $C_1, C_2, \dots, C_n$ are criteria, and x_{ij} refers to the rating of the alternative A_i in respect to criteria C_j. The weight vector $W = (w_1, w_2, \dots, w_n)$ involves individual weights w_j $(j = 1, \dots\dots, n)$ for each criterion C_j, satisfying $\sum_{j=1}^{n} w_j = 1$.

TOPSIS follows the following steps:

Step 1: Built the normalized decision matrix (NDM) $R = [r_{ij}]_{mxn}$, with $i = 1, \dots, m$ and $j = 1, \dots, n$. The normalized value r_{ij} is calculated as:

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}}, \tag{6}$$

with $i = 1, \dots, m$, and $j = 1, \dots, n$

The NDM *R* involves the relative rating of the alternatives. The weighted NDM $P = [p_{ij}]_{mxn}$, with $i = 1, \dots, m$, and $j = 1, \dots, n$ is calculated by multiplying the NDM by its related weights, after normalization. The weighted normalized value p_{ij} is computed as:

$$p_{ij} = w_i * r_{ij} \tag{7}$$

with $i = 1, \dots, m$, and $j = 1, \dots, n$

Step 2: Identify the positive ideal solutions A^+ (benefits) and negative ideal solution A^- (costs) as follows:

$$A^+ = (p_1^+, p_2^+, \dots, p_m^+) \tag{8}$$

$$A^- = (p_1^-, p_2^-, \dots, p_m^-) \tag{9}$$

where

$$p_j^+ = (\underset{i}{max}\, p_{ij}, j\epsilon J_1; \underset{i}{min}\, p_{ij}, j\epsilon J_2\,)$$

$$p_j^- = (\overset{min}{i} p_{ij}, j \epsilon J_1; \overset{max}{i} p_{ij}, j \epsilon J_2)$$

where J_1 and J_2 represent the *benefit* and *cost* of the criteria, respectively.

Step 3: Determine the Euclidean distances. This is the distance from the positive ideal solution A^+ and the negative ideal solution A^- of each alternative A_i:

$$d_i^+ = \sqrt{\sum_{j=1}^{n} (d_{ij}^+)^2} \tag{10}$$

$$d_i^- = \sqrt{\sum_{j=1}^{n} (d_{ij}^-)^2} \tag{11}$$

where

$d_{ij}^+ = p_j^+ - p_{ij}$, with $i = 1, \ldots, m$

$d_{ij}^- = p_j^- - p_{ij}$, with $i = 1, \ldots, m$

Step 4: Determine the relative closeness c_i for each alternative A_i with respect to the positive ideal solution using:

$$c_i = \frac{d_i^-}{d_i^+ + d_i^-} \tag{12}$$

Step 5: Identify the rank of the alternatives according to their relative closeness. Alternatives with higher c_i value are considered superior, as they are nearer to the positive ideal solution.

3. Numerical Results

The application begins by calculating the proportion (P_{ij}), and then the entropy (e_i) values. While calculating e_i values, a problem is encountered: Several P_{ij} values were undefined because of the X_{ij} = 0 values. Therefore, the following way to get rid of these zeros is proposed: Since the alternative with a high score in the benefit type criteria will be advantageous, $\frac{101}{101-X_{ij}}$ equation has been applied to calculate new non-zero X_{ij} values. In this manner, the alternative with a score of 100 will receive the highest value, while the alternative with a score of 0 will receive the lowest one. Similarly, since the alternative with the lowest value in the cost type criteria will be advantageous, $\frac{101-X_{ij}}{101}$ equation has been applied for the cost criteria. The weight of each criterion is calculated accordingly and given in Table 3. The distribution of the weights of the main criteria is presented in Figure 1.

The two major constituent criteria are data-driven and digital innovation (C_3) and social prosperity and inclusion (C_5). The former pertains to the adoption of digital technologies, while the latter addresses aspects of citizens' daily lives. Intriguingly, a detailed examination of the sub-criteria revealed that the two most significant criteria are: Stock market capitalization and renewable energy rate, which are not among C_3 and C_5.

Using TOPSIS, 48 cities were assessed based on 34 pre-determined indicators, as outlined in Table 2. The weights determined through the entropy method are presented in Table 3. In the initial phase of the assessment, the decision matrix was constructed, showcasing the performance values of each city per indicator. Subsequently, these values were weighted according to their corresponding values from Table 3. TOPSIS methodology leverages the best-performing cities to define the "positive-ideal solution" and uses the lowest performers for the "negative-ideal solution".

Table 3. Weight of the sub-criterion calculated using the entropy weight method.

	Weight		Weight		Weight		Weight		Weight		Weight		Weight
C_1	0,18667	C_2	0,09582	C_3	0,21101	C_4	0,13796	C_5	0,24901	C_6	0,01278	C_7	0,10662
C_{11}	0,02850	C_{12}	0,04688	C_{31}	0,03949	C_{41}	0,04111	C_{51}	0,02994	C_{61}	0,01278	C_{71}	0,03092
C_{12}	0,03860	C_{22}	0,01761	C_{32}	0,03997	C_{42}	0,03616	C_{52}	0,00485			C_{72}	0,02808
C_{13}	0,03276	C_{23}	0,03133	C_{33}	0,04433	C_{43}	0,02367	C_{53}	0,00197			C_{73}	0,04762
C_{14}	0,00630			C_{34}	0,04459	C_{44}	0,03222	C_{54}	0,02275				
C_{15}	0,03782			C_{35}	0,04263	C_{45}	0,00480	C_{55}	0,04315				
C_{16}	0,04269							C_{56}	0,04539				
								C_{57}	0,04397				
								C_{58}	0,02316				
								C_{59}	0,02513				
								C_{510}	0,00311				
								C_{511}	0,00559				

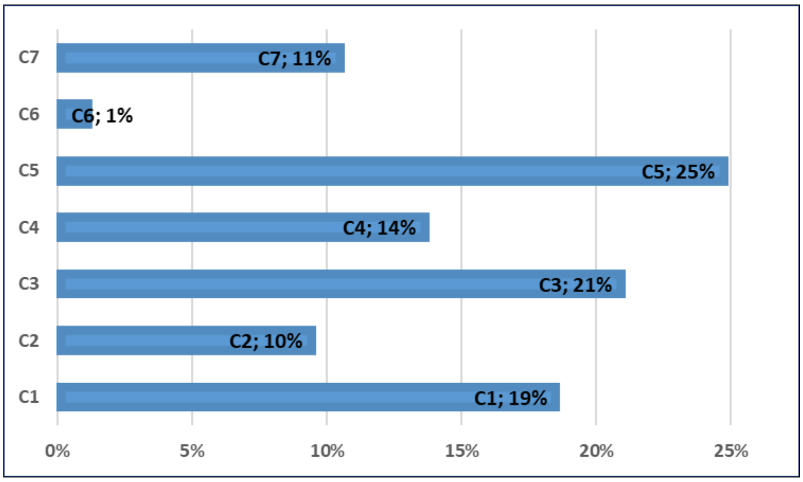

Figure 1. Distribution of criteria weights

A compact representation of the computational matrices that gives the ranking of cities in respect to each criterion is given in Table 4. It is noteworthy that New York City emerged as the "smartest" in our proposed methodology, it underperforms in the C_1 criteria. This suggests that New York City's digital infrastructure and services require substantial enhancements, and investments should channel in that direction. The data in Table 5 does not paint a rosy picture for İstanbul, which consistently ranks below 25th place across all seven dimensions. Given that the TOPSIS method integrates squared values into its evaluation to accentuate outliers, it might offer a more distinct differentiation between cities (Ye et al., 2022). The performances of various cities exhibit stark contrasts across different dimensions. For instance, Shanghai occupies the first or second spot in criteria C_1, C_4, or C_7; however, its performance in C_2 and C_6 is lackluster. A similar trend can be observed in Beijing, another Chinese city. Although it holds the 4th position in the overall ranking, it underperforms in criteria C_1, C_5, and C_7. Table 5 provides the computed distances of each city to ideal solution (d^+) and their distances to the non-ideal solution (d^-). A closeness coefficient nearer to 1 signifies a city's proximity to the positive ideal solution and its divergence from the negative ideal solution.

Table 4. Ranking of cities in respect to seven criteria based on distances calculated with TOPSIS

	C_1	Rank	C_2	Rank	C_3	Rank	C_4	Rank	C_5	Rank	C_6	Rank	C_7	Rank
1	Shanghai	0,56	Beijing	0,83	New York	0,80	Shanghai	0,62	London	0,76	Singapore	1,00	New York	0,81
2	Hong Kong	0,53	Tokyo	0,42	Tokyo	0,75	Beijing	0,59	New York	0,66	Hong Kong	0,98	Shanghai	0,62
3	Singapore	0,51	Paris	0,29	Los Angeles	0,75	New York	0,56	Singapore	0,46	Copenhagen	0,98	Tokyo	0,62
4	London	0,44	New York	0,22	Seoul	0,73	Tokyo	0,55	Dubai	0,41	New York	0,98	Hong Kong	0,62
5	Frankfurt	0,44	London	0,21	Chicago	0,71	London	0,48	Hong Kong	0,37	Boston	0,96	London	0,62
6	Dubai	0,42	Zurich	0,19	S. Francisco	0,71	S. Francisco	0,43	Tokyo	0,36	Chicago	0,96	Toronto	0,61
7	Seoul	0,41	Vienna	0,17	London	0,71	Hong Kong	0,40	Melbourne	0,32	S. Francisco	0,96	Paris	0,61
8	Stockholm	0,38	Helsinki	0,17	Singapore	0,70	Los Angeles	0,39	Los Angeles	0,30	Seoul	0,96	Mumbai	0,61
9	Paris	0,38	Stockholm	0,17	Boston	0,70	Washington	0,38	Sydney	0,27	Washington	0,96	Seoul	0,61
10	Copenhagen	0,37	Madrid	0,17	Washington	0,70	Moscow	0,37	Shanghai	0,27	London	0,95	Zurich	0,61
11	Sao Paulo	0,37	Seoul	0,16	Hong Kong	0,69	Singapore	0,36	Berlin	0,22	Los Angeles	0,93	Frankfurt	0,61
12	Taipei	0,36	Copenhagen	0,16	Sydney	0,69	Seoul	0,36	Seoul	0,22	Stockholm	0,92	Taipei	0,61
13	Amsterdam	0,36	Amsterdam	0,16	Paris	0,69	Bangkok	0,36	Paris	0,21	Melbourne	0,91	Sydney	0,61
14	Helsinki	0,35	Singapore	0,16	Beijing	0,69	Sao Paulo	0,36	Chicago	0,20	Sydney	0,91	Amsterdam	0,61
15	Vienna	0,35	Geneva	0,16	Osaka	0,69	Zurich	0,36	S. Francisco	0,20	Dubai	0,90	Stockholm	0,61
16	Tokyo	0,32	Frankfurt	0,15	Shanghai	0,69	Chicago	0,35	Vienna	0,19	Taipei	0,90	Singapore	0,61
17	Zurich	0,32	Toronto	0,14	Berlin	0,69	Geneva	0,34	Moscow	0,19	Helsinki	0,89	K. Lumpur	0,61
18	Milan	0,31	Boston	0,14	Melbourne	0,69	Boston	0,34	Stockholm	0,19	Berlin	0,88	Copenhagen	0,61
19	Los Angeles	0,31	Sydney	0,14	Taipei	0,69	Toronto	0,33	Amsterdam	0,19	Frankfurt	0,88	Jakarta	0,61
20	Brussels	0,30	Melbourne	0,14	Toronto	0,69	Paris	0,33	Geneva	0,18	Toronto	0,88	Johannesburg	0,61
21	Berlin	0,30	Berlin	0,14	Amsterdam	0,68	Copenhagen	0,32	Helsinki	0,18	Vancouver	0,88	Bangkok	0,61
22	Bangkok	0,30	Vancouver	0,14	Moscow	0,68	Mumbai	0,31	Toronto	0,18	Dublin	0,88	Dublin	0,61
23	New York	0,29	Taipei	0,13	Tel Aviv	0,68	Berlin	0,30	Zurich	0,17	Vienna	0,86	Milan	0,61
24	Geneva	0,29	Washingto	0,13	Sao Paulo	0,68	Vancouver	0,29	Washington	0,17	Osaka	0,86	Tel Aviv	0,60
25	**Istanbul**	0,28	Hong Kong	0,12	Stockholm	0,68	Sydney	0,29	Brussels	0,17	K. Lumpur	0,86	Helsinki	0,60
26	Jakarta	0,27	Dublin	0,12	Brussels	0,68	Madrid	0,29	Copenhagen	0,16	Fukuoka	0,85	Barcelona	0,60
27	Toronto	0,27	Shanghai	0,12	Zurich	0,68	Stockholm	0,28	Mexico City	0,16	Tokyo	0,85	Madrid	0,60
28	Chicago	0,26	Tel Aviv	0,12	Fukuoka	0,68	Barcelona	0,28	Madrid	0,16	Paris	0,83	Moscow	0,60
29	Dublin	0,25	Osaka	0,12	**Istanbul**	0,68	Melbourne	0,28	**Istanbul**	0,16	Beijing	0,83	S. Francisco	0,60
30	Madrid	0,25	Fukuoka	0,11	Vancouver	0,68	Amsterdam	0,28	Frankfurt	0,16	Tel Aviv	0,83	Fukuoka	0,60
31	K. Lumpur	0,24	S. Francisco	0,11	Vienna	0,68	**Istanbul**	0,27	Osaka	0,15	Geneva	0,83	**Istanbul**	0,60
32	Barcelona	0,24	Moscow	0,11	Dubai	0,68	Vienna	0,26	Dublin	0,15	Zurich	0,83	Mexico City	0,60
33	Vancouver	0,24	Brussels	0,11	Copenhagen	0,68	Dubai	0,26	Boston	0,15	Barcelona	0,82	Berlin	0,60
34	Sydney	0,23	Milan	0,10	Madrid	0,68	Frankfurt	0,26	Johannesburg	0,15	Madrid	0,82	Dubai	0,60
35	Mumbai	0,22	Chicago	0,10	Barcelona	0,68	Jakarta	0,25	Buenos Aires	0,14	Shanghai	0,82	Vancouver	0,60
36	Beijing	0,22	Dubai	0,10	Mumbai	0,67	Dublin	0,25	Vancouver	0,14	Amsterdam	0,82	Melbourne	0,60
37	Washington	0,22	Barcelona	0,10	Helsinki	0,67	Mexico City	0,24	Beijing	0,14	Brussels	0,80	Brussels	0,60
38	Melbourne	0,22	Buenos Aires	0,08	Geneva	0,67	Helsinki	0,24	Taipei	0,13	Bangkok	0,78	Boston	0,60
39	S. Francisco	0,21	**Istanbul**	0,08	Cairo	0,67	Osaka	0,24	Milan	0,13	Milan	0,67	Los Angeles	0,60
40	Moscow	0,21	Los Angeles	0,07	Frankfurt	0,67	Brussels	0,23	Barcelona	0,13	Mexico City	0,65	Vienna	0,60
41	Boston	0,21	Johannesburg	0,07	Jakarta	0,67	Fukuoka	0,22	Sao Paulo	0,12	Moscow	0,63	Geneva	0,60
42	Buenos Aires	0,21	Sao Paulo	0,06	Milan	0,67	Milan	0,21	Fukuoka	0,12	Mumbai	0,54	Sao Paulo	0,60
43	Osaka	0,19	. Lumpur	0,06	Dublin	0,67	Taipei	0,21	K. Lumpur	0,11	Jakarta	0,53	Beijing	0,60
44	Tel Aviv	0,18	Mexico City	0,06	Bangkok	0,67	Tel Aviv	0,21	Bangkok	0,11	**Istanbul**	0,44	Washington	0,60
45	Fukuoka	0,15	Cairo	0,05	Mexico City	0,67	Buenos Aires	0,15	Jakarta	0,11	Johannesburg	0,43	Chicago	0,60
46	Cairo	0,11	Bangkok	0,05	Johannesburg	0,67	K. Lumpur	0,14	Tel Aviv	0,10	Sao Paulo	0,28	Cairo	0,60
47	Mexico City	0,11	Mumbai	0,03	Buenos Aires	0,67	Cairo	0,14	Mumbai	0,09	Cairo	0,16	Osaka	0,60
48	Johannesburg	0,10	Jakarta	0,01	K. Lumpur	0,67	Johannesburg	0,12	Cairo	0,07	Buenos Aires	0,00	Buenos Aires	0,60

Surprisingly, Los Angeles ranks below İstanbul in criteria C_2 (Effective use of digital technologies and data) and C_7 (Market openness in digital business environments). Istanbul may have invested more in digital solutions related to public services, traffic management, or energy consumption compared to Los Angeles. Istanbul recently launched a Smart City Istanbul[3] platform, a central hub that provides real-time traffic updates, electricity/water consumption data, and other essential services, helping citizens optimize their usage and promoting transparency. The city of Istanbul installed sensors throughout its public transportation systems, effectively reducing congestion during peak hours by dynamically updating routes and schedules. While Los Angeles has numerous digital initiatives, it's possible they might have faced challenges in integrating and optimizing their digital services as efficiently as Istanbul. A major IT overhaul in the city's administration faced delays, leading to slower digital transformations compared to Istanbul.

Table 5. Overall ranking of cities based on distances calculated with TOPSIS

Rank	Cities	c_i	d^+	d^-
1	New York	0,60847	0,04823	0,07495
2	London	0,44695	0,06954	0,05620
3	Tokyo	0,41769	0,06901	0,04950
4	Beijing	0,36342	0,08286	0,04730
5	Singapore	0,32140	0,07950	0,03765
6	Shanghai	0,31640	0,08203	0,03797
7	Los Angeles	0,31366	0,07961	0,03638
8	Hong Kong	0,31176	0,07890	0,03574
9	Seoul	0,30928	0,08033	0,03597
10	Dubai	0,26252	0,09150	0,03257
11	San Francisco	0,25844	0,08799	0,03067
12	Paris	0,24490	0,08322	0,02699
13	Chicago	0,23605	0,08581	0,02651
14	Melbourne	0,21487	0,09075	0,02484
15	Boston	0,21128	0,09089	0,02435
16	Sydney	0,20962	0,08869	0,02352
17	Amsterdam	0,20585	0,09109	0,02361
18	Berlin	0,20274	0,09079	0,02309
19	Washington, DC	0,20268	0,09035	0,02297
20	Stockholm	0,19984	0,09372	0,02341
21	Zurich	0,19825	0,09335	0,02308
22	Copenhagen	0,19129	0,09534	0,02255
23	Toronto	0,18665	0,08980	0,02061
24	Frankfurt	0,18598	0,09346	0,02135
25	Vienna	0,18388	0,09405	0,02119
26	Geneva	0,18204	0,09710	0,02161
27	Helsinki	0,18077	0,09663	0,02132
28	Taipei	0,17976	0,09184	0,02013
29	Sao Paulo	0,17769	0,09458	0,02044
30	Moscow	0,17235	0,09280	0,01932
31	Brussels	0,16205	0,09460	0,01829
32	Dublin	0,16188	0,09669	0,01867
33	Osaka	0,16100	0,09198	0,01765
34	Madrid	0,15807	0,09399	0,01765
35	Vancouver	0,15717	0,09666	0,01802
36	**Istanbul**	**0,15271**	**0,09439**	**0,01701**
37	Bangkok	0,15037	0,09546	0,01689
38	Barcelona	0,14140	0,09583	0,01578
39	Milan	0,14117	0,09610	0,01580
40	Mumbai	0,13835	0,09612	0,01543
41	Jakarta	0,13760	0,09666	0,01542
42	Tel Aviv	0,12980	0,09605	0,01433
43	Kuala Lumpur	0,12720	0,09746	0,01420
44	Fukuoka	0,11909	0,09773	0,01321
45	Mexico City	0,11146	0,09617	0,01206
46	Buenos Aires	0,10958	0,09834	0,01210
47	Johannesburg	0,09188	0,09826	0,00994
48	Cairo	0,08467	0,09966	0,00922

Although Los Angeles is home to a thriving tech scene, it might face challenges like stricter regulations

[3] https://smartcity.com.tr/en/

or longer bureaucratic processes for digital startups, making it comparatively less open than Istanbul. The city may have higher barriers to entry for international digital businesses, given complex licensing or registration processes. It is also noteworthy that both Chicago and Washington, D.C. are among the bottom five in market openness (*C7*). Being the capital city, a significant portion of Washington, D.C.'s economy revolves around the federal government, which may not always align with the agility and innovation often associated with the digital business world. There might be a perceived talent gap in Chicago, with digital businesses feeling that they cannot source the right talent locally and face challenges in relocating talent due to high living costs or other factors.

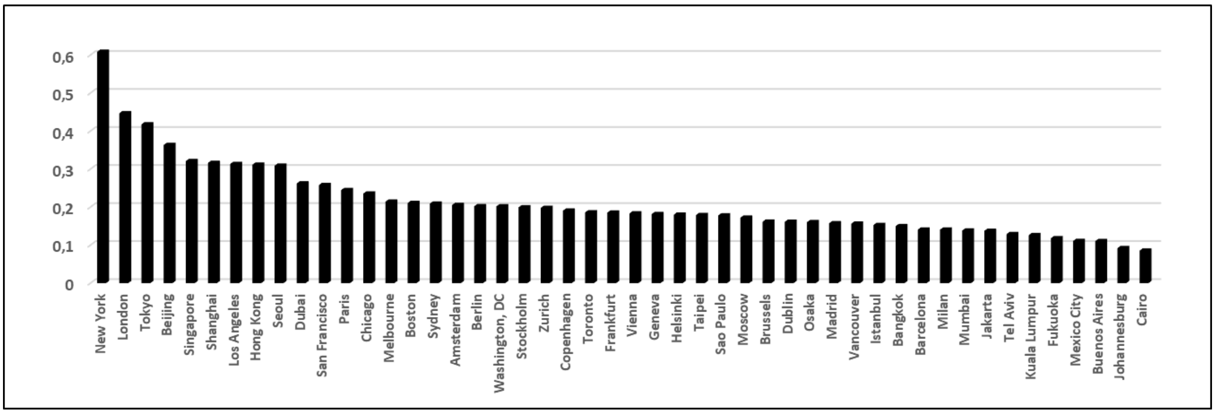

Figure 2. The general ranking of the cities

On a positive note, Seoul, Hong Kong, and Singapore demonstrate a consistently balanced and commendable performance across all dimensions. Conversely, Cairo, Buenos Aires, and Mexico City, which rank low in the overall smart city list, consistently fall short in all the evaluated dimensions. Interestingly, while Mumbai is positioned as the 40th smart city, it leaps to the 8th spot in criteria C_7. This suggests that Indian authorities might consider scrutinizing Mumbai's market conditions for potential replication in other Indian cities.

Based on the closeness to the ideal solutions in Table 5, the top three smart cities according to all criteria among the 48 are New York, London, and Tokyo, as visualized in Figure 2. İstanbul, the sole Turkish city on the list, ranks 36th.

4. Conclusion

Governments and local authorities were once primarily urged to invest in data-driven infrastructures and technologies to promote sustainability. Today, this has transitioned from a mere recommendation to a vital necessity. Yet, before allocating funds, cities must understand their position relative to their peers. This knowledge allows authorities to target investments effectively to addressed identified gaps. The methodology we present in this paper offers a straightforward way to compare cities globally. It aims to avoid subjective approaches relying on human assessments or expert judgments when determining the criteria weights and/or city performances. The goal is to determine how "smart" a city is in comparison to other major global cities. Our method ranks New York, London, and Tokyo as the top three out of 48 cities. The most similar study (Özkaya and Erdin 2020) listed London, New York, and Tokyo as their top three. Other related studies, even with different methods or data, usually include these cities in their top ten lists of smart cities worldwide. It is worth noting that İstanbul, the only Turkish city mentioned, is often ranked in the lower quartile. For instance, Aihemaiti and Zaim (2018) reviewed 40 randomly selected Turkish cities, and they placed Balıkesir first, while İstanbul was ranked 25th, again not in the top cities. Meanwhile, Adali et al (2022) selected 17 cities among the cities in GPCI, identified London, Paris, and Amsterdam as their leading cities, with Helsinki, Milan, and

İstanbul, at the tail end.

Instead of rankings solely based on one set of criteria, the initial phase of our proposed methodology seeks to curate a robust list of indicators. Our addition to the prevailing smart city discourse hinges on two pivotal facets: Firstly, we combine the Japanese and European perspectives in terms of indicators. Secondly, with a commitment to objectivity, we deploy the entropy weight method to fully negate human-centric biases. We believe that our ranking methodology will furnish decision-makers with a holistic and dependable ranking outcome.

In the literature, a smart city has been characterized by various aspects. To label a city as "smart," the chosen indicators must be scientifically valid, effective, encompassing, and apt. However, academic consensus remains elusive regarding a standardized set of smart city indicators or a definitive smartness index. This ambiguity serves as a limitation of our study, akin to other scholarly endeavors probing the smartness criterion for cities. The variance in indicator lists employed across different studies can drastically influence outcomes.

Future iterations of this work might contemplate the inclusion of additional smart city indicators and updated city performance metrics. If a consortium of smart city experts can be convened, their insights could be invaluable in assessing criteria to delineate importance weights. In scenarios where human subjectivity is unavoidable, methodologies anchored in fuzzy numbers might be leveraged to encapsulate the inherent subjectivity of expert perspectives.

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