A Framework Model for Evaluating Smart City Implementation Through the Lens of Sustainable Development*

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Abstract

The article introduces a methodological model for evaluating the effectiveness of smart city implementation through the lens of sustainable development. An innovative approach was applied, incorporating objective data analysis and residents' subjective perception of quality of life. The empirical research database was formed using the City Human Development Index and 15 components of the IMD Smart City Index, which are priorities for urban development. A cluster analysis was performed using the k-means method. The study analyzed indicators from 141 cities worldwide for 2024. As a result, cities were divided into two clusters: "progressive smart cities" and "transitional cities." Key success factors for urban transformations were identified, including housing affordability, corruption levels, transparency, education quality, security, and employment rates. The study concludes that the global dynamic is favorable for implementing the smart city concept and the effectiveness of related transformations within sustainable development. The proposed model is a practical tool for analyzing, monitoring, and planning urban infrastructure improvement strategies to improve citizens' well-being while ensuring the environment.

Keywords

Smart city, sustainable development, Smart City Index, City Human Development Index, cluster analysis, *k*-means, quality of life, framework model

1. Introduction

The global community faces unprecedented challenges – from climate change to depletion of natural resources and social inequality. This has led to a reevaluation of traditional development models, and the shift toward sustainable development principles aims to meet current generational needs while preserving the capacity of future generations to meet their own needs. The foundation of sustainable development rests on three core dimensions: economic growth, social inclusivity, and environmental sustainability.

The implementation and development of innovative technologies, especially the smart cities concept, is becoming a key factor for the successful realization of sustainable development principles in today's urbanized world. As cities strive to balance societal welfare, economic development, and environmental protection, smart technologies provide the necessary tools for transforming urban spaces and creating effective management systems. Smart cities represent an integrated system

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where digital technologies and communications systems are deployed to enhance city infrastructure and elevate the living standards of urban residents [3]. The deployment of sensor networks, IoT systems, and advanced data analysis makes possible more efficient management of energy consumption, traffic flows, water supply, and waste management. As an illustration, automated lighting infrastructure can adjust brightness depending on natural light and human presence, significantly minimizing power usage.

Smart mobility networks enhance public transport routes and regulate traffic lights in real time, reducing traffic bottlenecks and CO_2 emissions. Smart waste management systems use container fill sensors to optimize garbage truck routes, improving process efficiency and reducing environmental impact. A key component of intelligent urban environments is their ability to collect and analyze data for informed decision-making regarding urban planning and development [4]. This enables the creation of more resilient and adaptive urban systems that can effectively respond to environmental changes and citizens' needs. Through the implementation of smart technologies, cities become not only more efficient concerning resource usage but also more comfortable for living, fully aligning with sustainable development goals.

However, the smart city model is expanding widely beyond the simple implementation of technological solutions. The emphasis consistently remains on people and their needs, with technology serving only as a tool for creating a comfortable, safe, and inclusive urban space [5]. A smart city is an environment where every resident has access to quality services, can effectively interact with city administration, use convenient transport infrastructure, and actively be involved in community development. This is why evaluating the success of smart city concept implementation must consider such important aspects as accessibility of medical services, quality of education, cultural opportunities, and a sense of security among citizens. This allows cities to better understand the needs of their residents and adapt development strategies accordingly.

At the same time, a deep understanding of factors that influence citizens' perception of their cities' "smartness" becomes critically important for effective city planning and administration. This requires developing new methodological approaches and evaluation models that would consider not only objective indicators of technological development but also the subjective perception of quality of life by city residents. Such models must be flexible enough to adapt to the specifics of different cities while simultaneously enabling comparative analysis to identify the most successful practices in implementing the smart city concept. The article seeks to establish a framework model for identifying successful strategies and key indicators that influence the evaluation of smart city concept implementation effectiveness through the lens of sustainable development, based on the subjective perception of quality of life by city residents.

2. Related works

The application of smart city concepts for addressing complex urban environment problems and improving the quality of life for residents of large cities is widely discussed by scientists worldwide. Researchers J. S. Gracias et al. studied the current state and prospects of smart cities, evaluating the possibilities they offer [6]. J. Brodny et al. examined modern cities' complex problems regarding creating comfortable living and working conditions. In their study, they developed their methodology for assessing quality of life in 29 major Polish cities and created a ranking based on the developed Smart Sustainable Cities Assessment Scores system [7]. R. José and H. Rodrigues analyzed scientific publications, exploring the relationship between key challenges faced by smart cities and fundamental characteristics of digital innovations [8]. J. Colding studied ways to increase the inclusivity and accessibility of smart cities for all residents, focusing particularly on the needs of marginalized groups facing digital inequality [9]. D. Scala et al. conducted research on educational systems within the smart city context to identify current trends, research communities, and most demanded research directions [10]. Z. Shen and co-authors presented a comprehensive solution for creating an optimal system in the form of a virtual urban community. This solution aims to support developing countries in overcoming challenges related to population aging through increasing urban environment inclusivity [11]. Authors M. Zaman et al. conducted a comprehensive review of the smart city framework, emphasizing using Internet of Things (IoT) technologies for their development and management. The research results include developing a general IoT-based smart city architecture, evaluating success criteria for such projects, and identifying the main challenges and benefits of implementing these technologies in real urban conditions [12]. L. Hammoumi applied artificial intelligence methods to evaluate smart cities' effectiveness and determine factors influencing their "smartness" level [13]. R. Wolniak and K. Stecuła analyzed literature regarding artificial intelligence use in smart cities, covering six main areas: smart mobility, smart environment, smart governance, smart lifestyle, smart economy, and smart people. They noted that cities need individual approaches to implementing smart technologies due to differences in key goals, data use, citizen engagement, service automation, approaches to sustainable development, security and compliance with standards, integration of newest technologies, predictive analytics, economic growth, and inclusive solutions [14]. O. Bafail investigated key factors affecting smart city program success by analyzing data from 140 urban centers using machine learning and regression analysis methods. He emphasized that the Human Development Index (HDI) is the main indicator of the effective sustainable development of smart cities [15]. F. Shi and W. Shi examined 33 modern smart city evaluation frameworks and conducted their comparative analysis according to key criteria. The conclusions emphasize the necessity of these criteria as guidelines for improving evaluation models and supporting developers and decision-makers in choosing appropriate frameworks [16]. Researchers O. Dashkevych and B. A. Portnov stated that despite extensive research into the smart city approach, there is still a significant gap in our understanding of concrete, measurable criteria that can both classify a city as “smart” and quantify its level of “smartness” [17]. The papers [18-19] present approaches to analyzing drone operations in cities. Modeling the process of air pollution by harmful emissions from vehicles shown in [20].

Assessing how effectively smart cities contribute to sustainable development goals is a nuanced and complex challenge. A key consideration is finding the right equilibrium between two primary factors, with special consideration of the degree of implementation of innovative technological solutions and ensuring citizens' satisfaction with living conditions in their cities. While many scientific publications are dedicated to the first aspect, the second one has only been studied fragmentarily and requires additional comprehensive research. The improvement of existing frameworks for evaluating smart cities' effectiveness to adopt effective strategies for sustainable development objectives continues to be a relevant issue.

3. Methodology

The research applies a holistic methodological approach to measure the success of smart city initiatives in advancing sustainable development objectives. The methodology is based on using three main tools:

1. IMD Smart City Index (SCI) [21] for evaluating the success of smart technology implementation, which is based on measurable indicators and considers citizens' subjective perception of urban environment quality.
2. City Human Development Index (city HDI) [22] for determining the level of societal well-being in urban spaces.
3. *K*-means cluster analysis for grouping cities with similar characteristics [23]. The empirical analysis was conducted based on City HDI and 15 components of the IMD SCI, which are priorities for city development, utilizing RapidMiner Studio to analyze data and machine learning platform [21].

This approach allows for a comprehensive analysis of both objective measures of the development of urban infrastructure and the subjective experience of life quality by city residents, which is key to understanding the success of smart city concept implementation. The innovation of this approach lies in its emphasis on analyzing indicators that reflect citizens' sense of life satisfaction in their cities. This enables the identification of not only technical aspects of smart city development but also the evaluation of their impact on citizens' daily lives, emotional well-being, and social cohesion.

3.1. Smart City Index

The SCI is one of the primary international rankings that evaluates the success of technology implementation in enhancing city dwellers' wellbeing. It is developed by the Institute for Management Development (IMD). The SCI calculation methodology is founded on an integrated approach considering two fundamental aspects of smart city development. The first component, "Structures", reflects the existing infrastructure and technological innovations of the city. The assessment includes five key areas of urban life: technological capabilities, mobility, health and safety, economic activity, and urban governance. The second component, "Technologies", focuses on measuring the real-world effect of the implemented measures and smart solutions on citizens' daily lives. This aspect is investigated through extensive surveys of city residents regarding their experience with city services, transportation systems, and job prospects and their associated perception of safety levels and environmental conditions in the city [21].

The rating formation process includes collecting and analyzing data from various sources. The foundation is a survey of city residents, where 100 to 120 respondents participate in each city. Their responses are supplemented by objective economic and social indicators of city development, as well as technological indicators such as internet coverage levels and Wi-Fi network availability. To ensure objectivity in comparison, all indicators are standardized on a scale from 0 to 100. After this, weighted average values are calculated for each sphere, and the city's final score is determined as the arithmetic mean of scores across all categories. An important feature of the methodology is the grouping of cities by level of economic development, which allows for more accurate comparisons between cities with similar economic conditions.

The annual ranking update allows for tracking the progress of cities in implementing smart technologies and their impact on the living standards of the population. The index has become an important tool for city authorities and policymakers, helping them evaluate the effectiveness of implemented solutions and identify priority areas for further development. Additionally, the ranking results promote the sharing of best practices among cities and stimulate healthy competition in the field of smart urban development [21].

3.2. City Human Development Index

The City HDI represents a customized version of the Human Development Index (HDI), purposefully created to evaluate development at the city level. This metric assesses a city's progress across three core dimensions of human advancement while accounting for the unique characteristics of urban environments. The index incorporates three key components of urban development. The first is health and longevity, evaluated through life expectancy at birth and access to healthcare services within the city. The second focuses on education, measured by urban literacy levels and accessibility of educational opportunities within the city. The third dimension examines living standards, assessed by per capita gross urban product [22].

Additionally, the City HDI integrates specific urban elements including infrastructure availability and housing conditions, air pollution levels, and presence and accessibility of communal areas. This approach, which examines the presence and accessibility of communal areas, provides deeper insights into urban well-being than relying solely on the HDI. City HDI scores range from 0 to 1, with higher values indicating greater levels of human development in the urban context. As a vital tool for urban development and governance, the City HDI values fall between 0 and 1, where higher scores reflect enhanced levels of development across city spaces. This also identifies key areas where interventions are needed to enhance city dwellers' living conditions, making it an essential resource for informed decision-making [22]. Analysis of techniques for data processing in a smart city using the Internet of Things is considered in [27-30].

3.3. K-Means clustering methodology

Cluster analysis is a technique within machine learning, which represents a branch of artificial intelligence. It is used for grouping data according to their shared characteristics or distinctions. This unsupervised machine learning approach categorizes elements into groups by identifying their shared features. Cluster analysis enables the identification of similarities between data elements without requiring predefined labels or categories. The clustering process involves calculating the measure of proximity or similarity between objects, allowing them to be grouped in such a way that elements within one cluster are more similar to each other than to elements in other clusters. Among the most common cluster analysis algorithms is *k*-means.

The *k*-means algorithm is among the most commonly used unsupervised learning techniques for clustering data. It partitions a dataset into *k*-distinct, non-overlapping clusters based on minimizing the variance within clusters. The method assumes that each cluster is spherical and is represented by its centroid, which is the average position of all points in the cluster [23].

3.3.1. Mathematical formulation

Given a dataset $X = \{x_1, x_2, \ldots, x_n\}$, where each $x_i \in R^d$ is a data point in d-dimensional space, the goal is to partition the data into k-clusters $\{C_1, C_2, \ldots, C_k\}$ by minimizing the following objective function:

$$J = \sum_{j=1}^{k} \sum_{x_i \in C_i} \left\| x_i - \mu_j \right\|^2, \tag{1}$$

where μ_j is the centroid of cluster C_j, calculated as:

$$\mu_j = \frac{1}{|C_j|} \sum_{x_i \in C_i} x_i, \tag{2}$$

where $\left\| x_i - \mu_j \right\|^2$ represents the squared Euclidean distance between a data point x_i and its cluster centroid μ_j;

J is the total within-cluster sum of squares, which the algorithm seeks to minimize.

3.3.2. Algorithm steps

1. Initialization: select k-initial cluster centroids randomly or use methods like k-means to improve convergence.
2. Assignment: assign each data point x_i to the closest cluster according to the Euclidean distance:

$$C_j = \left\{ x_i : \left\| x_i - \mu_j \right\|^2 \leq \| x_i - \mu_l \|^2, \forall l = 1, \ldots, k \right\}. \tag{3}$$

3. Centroid Update Step: update the centroids by recalculating the mean of each cluster:

$$\mu_j = \frac{1}{|C_j|} \sum_{x_i \in C_i} x_i, \tag{4}$$

4. Repeat: steps 2 and 3 are iteratively repeated until convergence, typically when there is no significant change in cluster centroids or the assignment of points.

Cluster analysis allows for the identification of hidden patterns, and segmentation of data based on specific features, and contributes to a deeper understanding of the structure under study object or phenomenon [23].

3.4. Data selection and description

To determine the most important indicators that shape city residents' positive perceptions about the quality and comfort of life in their cities, which impact the evaluation of smart city initiative implementation success, we analyzed the city HDI and 15 basic SCI components for 2024 across 141 cities worldwide. These are the following indicators that respondents identified as priorities for their city's development [21]:

- affordable housing (AH);
- air pollution (AP);
- basic amenities (BA);
- citizen engagement (CE);
- corruptions/transparency (CT);
- fulfilling employment (FE);
- green spaces (GS);
- health services (HS);
- public transport (PT);
- recycling (RE);
- road congestion (RC);
- school education (SE);
- security (SEC);
- social mobility/inclusiveness (SMI);
- unemployment (UN).

The values of these indicators are determined by the percentage of respondents who regard the respective area as one of the most important and relevant for their city's development.

Figure 1 shows a sample of the raw data structure.

city HDI	UN	HS	SE	AH	CT	SEC	BA	FE	RC	AP	PT	GS	RE	CE	SMI
0.521	66.800	63.200	59.600	50.100	47.200	36.800	35.900	28.900	28.500	17.600	13.300	11.100	9.700	8.800	3.800
0.636	66.900	59.900	14.900	52.100	57.900	62.900	68.300	34.400	30	12.200	11.500	3.800	5.500	9.100	4.100
0.646	65.300	49.400	20	71.300	58.100	77.900	39	28.800	19	6.900	15.500	5	10.500	15	7.500

Figure 1: Fragment of the input dataset.

4. Results and discussion

As a result of the conducted cluster analysis, 2 clusters were identified (Fig. 2).

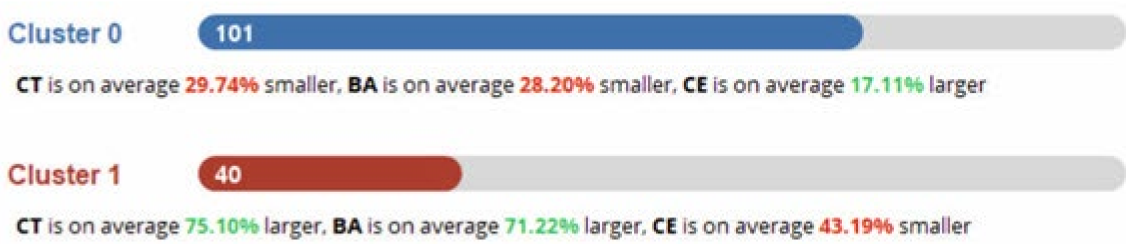

Figure 2: *K*-means: summary

Cluster No. 0 included 101 cities: Amman, Chongqing, Seattle, Guangzhou, Shenzhen, Zhuhai, Hangzhou, Nanjing, Muscat, Tianjin, Ankara, Doha, Istanbul, Jeddah, Mecca, Medina, Lille, Shanghai, Krakow, Belfast, Nicosia, Cardiff, Bordeaux, Lisbon, Riyadh, Newcastle, Beijing, Leeds, Phoenix, Abu Dhabi, Dubai, Zaragoza, Birmingham, Vilnius, Lyon, Manchester, Milan, Barcelona, Taipei City, Tel Aviv, Glasgow, Kiel, Budapest, Montreal, Philadelphia, Bologna, Warsaw, Chicago, Riga, Hanover, Luxembourg, Los Angeles, San Francisco, Bilbao, Tallinn, Busan, New York, Dusseldorf, Singapore, Madrid, Washington D.C., Rotterdam, The Hague, Denver, Vienna, Ottawa, Toronto, Bratislava, Brisbane, Gothenburg, Vancouver, Hong Kong, Melbourne, Boston, Paris, Dublin, Munich, Auckland, Seoul, Sydney, Brussels, Ljubljana, Wellington, Berlin, Reykjavik, Helsinki, Prague, Amsterdam, Geneva, Lausanne, Copenhagen, Hamburg, Stockholm, London, Canberra, Oslo, Zurich, Milan, Barcelona, Taipei City, Tel Aviv, Glasgow, Kiel, Budapest, Montreal, Philadelphia, Bologna, Warsaw, Chicago, Rome, Kuala Lumpur, Hanoi, Rio de Janeiro, .

Cluster No. 1 was formed by the following 40 cities: Sana'a, Nairobi, Abuja, Hyderabad, Islamabad, Bengaluru, Beirut, Lagos, Mumbai, Makassar, Rabat, Accra, Medan, Ho Chi Minh City, Delhi, Chengdu, Guatemala City, Cape Town, Medellin, Jakarta, Manila, Algiers, Tunis, Cairo, Sao Paulo, Buenos Aires, Mexico City, Brasilia, Lima, San Jose, Bangkok, Sofia, Santiago, Marseille, Athens, Zagreb, Bucharest, Osaka, Tokyo, Bogota.

Table 1 shows the average values of the analyzed data for the identified clusters.

Table 1
K-means centroid table

Cluster No.	AH	AP	BA	CE	HDI	CT	FE	GS
0	70.37	29.61	21.16	13.93	0.92	23.19	29.60	20.58
1	41.54	34.15	38.42	8.82	0.76	46.16	29.21	18.71

Cluster No.	HS	PT	RC	RE	SE	SEC	SMI	UN
0	39.80	28.69	45.38	19.50	24.05	39.99	15.28	35.18
1	46.66	27.18	39.51	17.11	22.96	52.52	9.51	46.61

The characteristics of city distribution across clusters indicate significant differences in affordable housing availability among cities belonging to different groups. Smart cities in cluster No. 0 exhibit noticeably better performance in the area of affordable housing, in comparison to cities in the 2nd cluster. This implies that residents of the 1st group of cities have broader access to housing at reasonable prices and better opportunities to purchase or rent accommodations that align with their income levels. Such a situation may result from more effective housing policies, better urban planning, or the successful implementation of social housing programs in cluster Zero cities. As per the World Economic Forum report "Global Risks Report 2024", the cost-of-living crisis remains one of the key challenges for 2024 [25]. This highlights the importance of implementing smart initiatives and identifying key performance indicators for successful urban strategies.

Cities in cluster No. 0 demonstrate higher levels of citizen engagement, City HDI, security, green spaces, public transport, road congestion, recycling, school education, and social mobility (inclusiveness). At the same time, smart cities in this group are characterized by reduced air pollution levels, essential amenities, corruption/transparency, health services, and unemployment compared to cities in cluster 1. The perception of meeting employment among residents of the cities in both identified clusters shows almost no difference (Fig. 3).

The analysis of the overall characteristics of cities in different clusters revealed a clear differentiation across many key indicators. Cities belonging to cluster No. 0 demonstrate advantages in numerous aspects of quality of life and urban development. These cities exhibit higher levels of citizen engagement in urban processes, a better HDI, and a larger number of green areas. Their transportation systems are also more developed, although they experience higher levels of road congestion. Additionally, these cities outperform in security, waste recycling, school education, and social mobility.

Conversely, these same cities demonstrate lower performance in some problematic areas compared to the smart cities of the 1st cluster. In particular, they experience lower levels of air pollution, a less developed basic infrastructure, fewer issues with corruption and transparency, as well as lower unemployment rates, and better healthcare quality indicators. Interestingly, despite all these differences, the perception of fulfilling employment remains almost identical for residents of both clusters, indicating a similar degree of subjective job satisfaction regardless of other urban indicators.

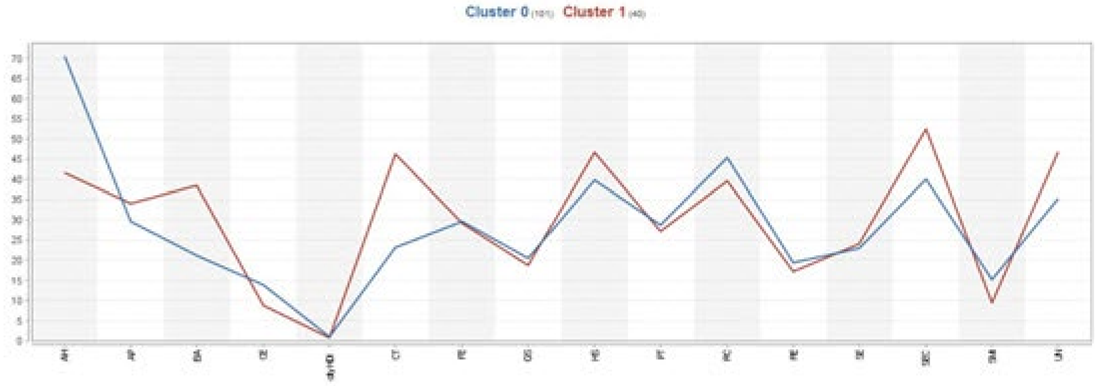

Figure 3: *K*-means centroid chart

From the *k*-means scatter plot presented in Figure 4, it can be inferred that the distribution of smart cities into the identified clusters was performed correctly: the data in the space is well-separated into clusters. Each group exhibits certain patterns: the blue points (cluster 0) are predominantly located in the lower section of the graph, while the red points (cluster 1) show higher values along one or two axes. This indicates that the algorithm has identified specific patterns in the distribution.

There is no substantial overlap between the clusters. The boundary between the data groups is visible, which indicates the effectiveness of the *k*-means method.

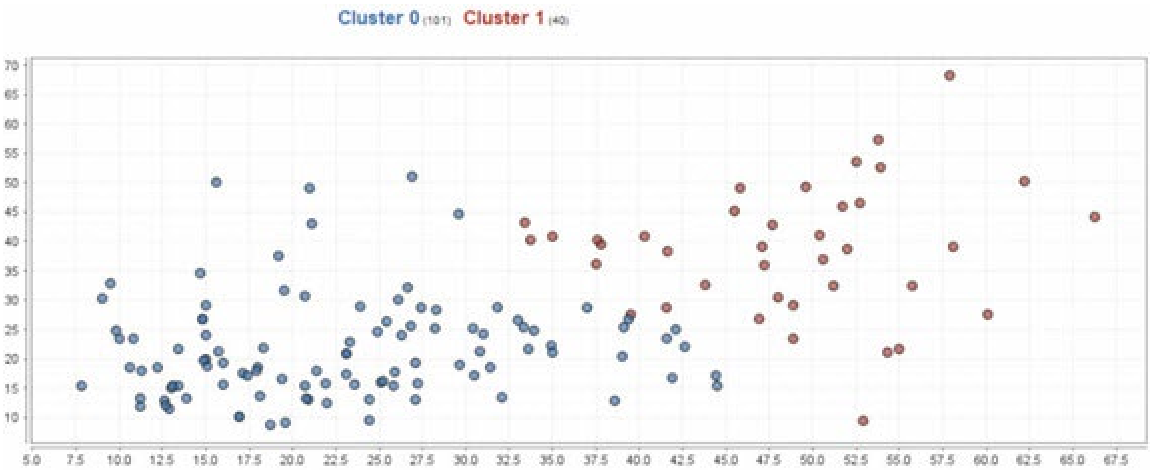

Figure 4: *K*-means scatter plot

The framework of the classification tree hierarchically demonstrates how different factors influence the assignment of a city to a particular cluster.

Key nodes of the tree:

1. Corruption/transparency. This is the root node of the tree, determining whether the indicator value exceeds 47. If the value is ≤ 47, the tree considers the next criterion, city HDI. If the value is > 47, the distribution proceeds according to the affordable housing value.
2. Affordable housing. If this indicator's value is ≤ 79.800, the city is allocated to cluster 1; otherwise, it belongs to cluster 0.
3. City HDI. If the value of this metric is ≤ 0.735, the city falls into cluster 1. If the value is > 0.735, the degree of school education is evaluated next.
4. School education. If the value is > 43.350, the city belongs to cluster 1. If it is a value ≤ 43.350, the next criterion considered is unemployment.
5. Unemployment. When the unemployment rate is > 66.800, the city is grouped into cluster 1. Otherwise, the distribution continues according to the security indicator.

6. Security. The boundary of 78.150 determines further distribution: if the Security value exceeds the threshold, the city belongs to 1st cluster. Otherwise, the tree proceeds to the Social Mobility/Inclusiveness node.

7. Social mobility/inclusiveness. If this indicator's value is ≤ 5.450, the city is grouped into 1st cluster. Otherwise, the decision moves to the next node.

8. Health Services. This is the final criterion used for distributing cities into the tree's branches. The limit of 39.200 determines the cluster: if the value is ≤ 39.200, the city belongs to cluster 0; otherwise, it is grouped into 1st cluster.

Figure 5 depicts a classification tree that illustrates the process of separating smart cities into two clusters.

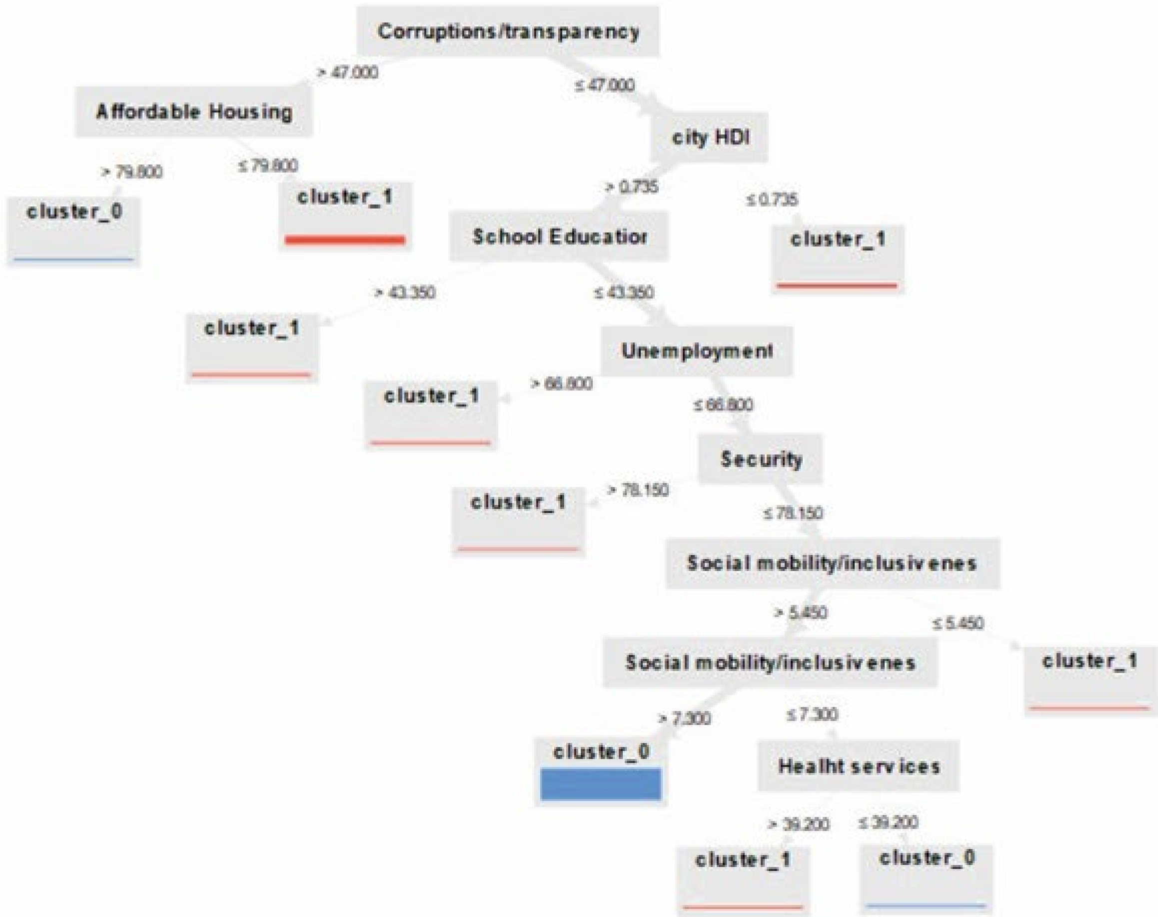

Figure 5: *K*-means cluster tree

The analyzed smart cities have been categorized as follows:

Cluster 0 – “Progressive Smart Cities”. These cities are characterized by elevated levels of digital and social development, active citizen engagement, advanced environmental infrastructure, and a high standard of life. They encounter specific challenges related to essential infrastructure and healthcare services.

Cluster 1 – “Transitional Cities”. These cities demonstrate better indicators in basic infrastructure and healthcare services but exhibit lower performance in areas such as environmental sustainability, education, and social integration. This suggests their intermediate status in the transformation process toward becoming fully developed smart cities.

The obtained assessments support conclusions from other researchers that different cities implement various smart strategies of cities [26]. Thus, comprehensive and multidimensional studies are necessary to determine effective urban development practices that incorporate a human-centered approach and sustainable development goals. Resident satisfaction with the quality and comfort of life in their cities is a key indicator of a smart city's development level. The evaluations presented in this article can be employed to create smart city strategies aimed at creating the most comfortable living conditions for residents and visitors. They can also act as a basis for further investigation into the implementation of smart city initiatives.

5. Conclusions

The article presents a framework model for evaluating the effectiveness of implementing The smart city concept in the context of sustainable development, derived from the analysis of residents' subjective perceptions of quality of life, allowing the identification of key factors for the success of urban transformations.

The proposed methodology, which combines the examination of IMD SCI, city HDI, and *k*-means clustering, effectively differentiated 141 cities worldwide into two clearly defined clusters: "progressive smart cities" and "transitional cities." It was found that the main factors affecting residents' life satisfaction in smart cities and determining the success of the implementation of the smart city concept are influenced by factors such as the level of corruption/transparency, the city's HDI, the quality of school education, the unemployment rate, and safety. These indicators serve as the main criteria for dividing cities into clusters. Cluster No. 0 ("progressive smart cities") demonstrates higher indicators in areas such as citizen engagement in urban processes, green space development, public transport quality, waste recycling, school education, safety, social mobility, and inclusiveness. "Transitional cities" (cluster No. 1) are characterized by better indicators in basic infrastructure and healthcare services but show lower performance in the areas of ecology, education, and social integration, indicating their intermediate state in the transformation process toward fully developed smart cities. The significant predominance of cities in the first cluster (101 cities) compared to the second cluster (40 cities) indicates a positive global trend in the implementation of the smart city concept and the success of related transformations within the framework of sustainable development. The study highlighted the significance of considering not just objective indicators of urban infrastructure development but also residents' subjective perceptions of assessing the effectiveness of the smart city concept implementation.

The proposed methodology can be utilized by cities to assess the current state of smart initiatives, identify priority areas for improving urban infrastructure, develop strategies to enhance residents' living standards, as well as for benchmark and exchange best practices with other cities. The research results provide a foundation for further exploration of the factors contributing to the successful implementation of the smart city concept and the formulation of recommendations for increasing the efficiency of urban transformations in the framework of sustainable development.

Future research will focus on identifying the relationship between the effectiveness of smart city implementation and the degree of digital maturity of countries, based on a comparative analysis of the IMD SCI and the IMD World Digital Competitiveness Ranking.

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Declaration on Generative AI

The authors have not employed any Generative AI tools.

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