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Development and application of an integrated smart city model

Azzam Abu-Rayash *, Ibrahim Dincer

Clean Energy Research Laboratory (CERL), Faculty of Engineering and Applied Science, Ontario Tech. University, 2000 Simcoe Street North, Oshawa, Ontario, L1H 7K4, Canada

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ABSTRACT

This study presents an innovative integrated approach for smart cities, aimed at promoting environmentally sustainable economies through novel technological and socio-economic transitions. The proposed model determines the smart city index (SCI) by aggregating 32 distinct performance indicators that significantly transform the environment, economy, energy, social, governance, and transportation sectors. This model is inherently multidisciplinary and is methodologically processed using multi-criteria decision analysis, which is aggregated using four distinct weighting schemes. The model results reveal that based on the equal weighting scheme, Sydney emerges as the city with the highest SCI score of 0.72, whereas Lima is identified as the city with the lowest SCI score of 0.26. On the other hand, based on the sustainability triad scheme, Toronto tops the list with an SCI score of 0.77, whereas Abuja scores the lowest with an SCI score of 0.31. Interestingly, Toronto, Vancouver, and Montreal continue to maintain their position among the top 5 cities across all three schemes: equal weighting, sustainability triad, and energy-focused schemes. Furthermore, the energy-focused scheme identifies Montreal as the top-performing city, scoring 0.7, followed by Oshawa at 0.67, and four Canadian cities top the SCI scores in this scheme. In contrast, Lima still remains at the bottom of the list with an SCI score of 0.27. Finally, based on a smart health-focused scheme, Sydney, Osaka, and Hämeenlinna rank highest in SCI scores. Overall, the proposed approach and model provide valuable insights and guidelines for policy-makers and urban planners to design and implement smart city initiatives that can significantly enhance sustainable development and improve quality of life in urban settings.

1. Introduction

As expected, renewable energy solutions are now more cost effective than before. In fact, the IRENA's report [1] emphasizes that unsubsidized renewable energy is the most frequent and cheapest source for energy generation. The cost of installation and maintenance of renewables continues towards a downward trajectory, leading to mass adoption. Their report findings show a decrease in the global weighted average cost of electricity by 26% for concentrated solar power (CSP), followed by 14% for bioenergy, 13% for photovoltaic (PV) and onshore wind, 12% for hydropower, and finally 1% for geothermal and offshore wind [1].

Lund et al. conducted a review study on smart energy systems published in the literature and found that the smart energy system concept represents a paradigm shift in energy management [2]. They also conclude that smart energy systems are those that follow an integrated and holistic approach by integrating the energy need of multiple sectors and treating them. For example, the energy needs for the industrial, residential, commercial and transportation sectors would be addressed altogether and not in silos. Therefore, a

* Corresponding author.
E-mail address: Azzam.aburayash@ontariotechu.net (A. Abu-Rayash).

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notable feature of smart energy systems is the holistic and integrated approach from a sectorial perspective. Smart city frameworks have been applied globally throughout key areas such as infrastructure, data, services and devices, where India and China both prioritize infrastructure and data, the United States and Europe both prioritize services, devices and data sequentially [3].

Dincer and Acar conducted research on smart energy systems and identified several key expectations for these systems, including being exergetically efficient [4]. They emphasized the importance of ensuring that these systems are "smart" throughout every stage of the energy process, from generation to conversion to distribution and usage. In a related study, Dominković et al. developed a model that examined the interactions between various sectors [5]. The researchers also created models for five different large-scale storage systems, and used linear optimization to determine the optimal share of district energy, energy efficiency, and renewable supply. In addition, Connolly et al. conducted research on the most effective and cost-efficient methods for integrating renewable energy into the energy system [6]. Their integrated energy system features multiple energy sources including bioenergy fuels, wind and solar that meets the basic demands of mobility, power, cooling and heating. Electrifying the transportation sector is highlighted as necessary to achieve the smart energy system objective. This can be done by using electro fuels or intermediate storage medium such as hydrogen. The authors also argue that electricity storage leads to the most expensive form of energy storage, which is 100 times more expensive than thermal storage. A novel IoT (internet of things)-based model for healthy development index for urban cities is proposed by Ref. [7], where they use a Gaussian-based approach to forecast urban cities developments.

Between 2010 and 2020, there have been over 150 articles published considering smart city assessment, as stated in Ref. [8]. They also conclude that the proposed future research agenda revolve around smart city performance measurement framework, composite index for smart sustainable cities, and a holistic evaluation using indicator setting. These gaps are addressed in this paper subsequently. The smart city concept can be very subjective and ambiguous. In fact, the researchers in Ref. [9] have explored the perceived understanding of 113 Belgian municipalities on their understanding of smart cities. Their results show that municipalities view the smart city concept from four viewpoints: technological, societal, comprehensive, and nonexistent. In fact, a comprehensive methodology for planning and assessing the development of smart energy systems leading to complex energy provision technology networks using both on-site and off-site resources is proposed by Ref. [10]. In their study, various energy sources including a solar system, coupled with an industrial waste heat recovery system along with grid-based resources such as district heating, natural gas and electricity are all combined. In addition, this case study features centralized technologies such as large-scale combined heat and power and district heating and decentralized technologies such as boilers and solar collectors. Their results show that decentralized systems with low-temperature waste heat and decentralized heat pumps in buildings are most feasible financially and ecologically. These results can be questionable as centralized systems such as district heating and cooling are proven to be more environmentally benign with larger financial investments needed. Methods used in this study include the Process Network Synthesis (PNS), the Energy Long-term Assessment of Settlement Structures (ELAS), and the Sustainable Process Index (SPI). On the other hand, smart cities in future energy system architecture are explored by Ref. [11], where they investigate the impact of future electric power systems on production, storage, transmission, distribution and consumption of electricity. In addition, MCDA is utilized to assess the sustainability of cities by Ref. [12], by integrating energy, environment and infrastructure parameters. The environmental problems arising from the concept of sustainability, namely from water, energy and environmental aspects are investigated by Ref. [13]. The balance between energy consumption, population growth and deforestation, desertification and other natural phenomena is discussed in Ref. [14].

A stand-alone smart energy system was designed and assessed for a remote hospital, by utilizing the hospital's daily waste of 0.6 tons, coupled with PV system, biogas cofire and diesel generators. The optimization study indicates a carbon emission and diesel consumption reduction by almost 84% and 81%, respectively [15]. Circular economy city concept is evaluated by Ref. [16] as a proposed solution to heightened rates of urbanization and climate change. The developed framework suggests that experimentation, knowledge development activities and strong policy strategies are critical in the development of circular economies. Moreover, assessment of 18 large-scale post carbon economy transition strategies is conducted by Ref. [17], who analyzed the targets, technologies, costs, equity, governance and social change aspects of the 18 strategies. Results illustrate that technology and costs are not key transition barriers. On the other hand, strategies do not adequately represent the pathways for rapid societal change [18]. In fact, technological and governance domains dominate the smart city research and continue to be integral components for smart city development [19].

The key goal of this research is to develop a practical and feasible model for a net zero energy-based smart city. The paper has four specific objectives to achieve this goal:

- To develop a new methodology for characterizing smart cities and evaluating their performance across eight key domains.
- To examine the socio-economic transitions necessary to foster an environmentally sustainable economy.
- To conduct parametric studies to evaluate the model's resiliency and explore the relationships between variables and domains, specifically within the environmental and economic domains.
- To analyze the economic, technical, and environmental considerations relevant to smart cities.

The strengths and hence novelties of this paper revolve around the introduction of a newly developed holistic approach for assessment of the world's cities under a performance criterion of smart city index (SCI). Furthermore, the meticulous journey of data collection for twenty cities worldwide for each individual indicator is considered unique and innovative for this study. Since this model is novel, the data analyses and parametric studies between the individual variables and domains add more to the robust nature and reliability of the model. Despite the novelty of this research, limitations of the study include the time the data sets were collected, which were primarily for the year of 2020. It is important to note that most of the data sets was currently available while some data points were missing for some cities.

2. Model development and methodology

The smart city index that is proposed in this paper is composed of eight main dimensions, each is assessed by four distinct indicators, totally 32 performance indicators. Data is obtained at the granular level for 20 cities across the world and computed using multi-criteria decision analysis (MCDA) to aggregate a final smart city index. Such aspects are described in detail in Fig. 1 and are listed as follows:

- Smart Environment
- Smart Economy
- Smart Society
- Smart Governance
- Smart Energy
- Smart Infrastructure
- Smart Transportation
- Smart Health

For the information obtained to be reliable, the process must be meticulously methodical and quantified. Additionally, indicators must be thoughtfully chosen using a logical and systematic approach to accurately represent each aspect of the smart city, while also ensuring simplicity and reliability of the model. Indicators serve as tools that enable researchers to summarize and simplify complex, dynamic information into meaningful and useful data. To achieve optimal results, ten guiding principles are followed. Fig. 2 depicts these steps.

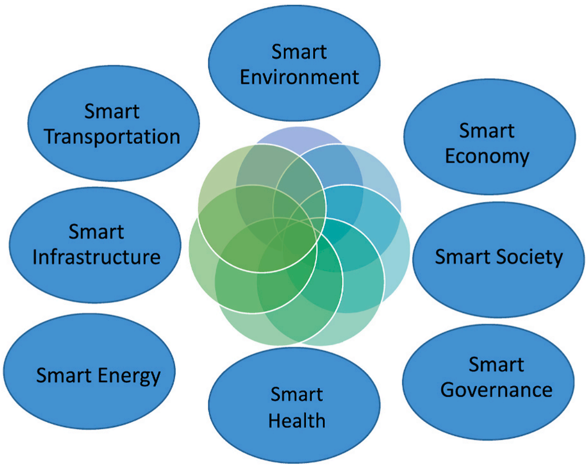

Fig. 1. The aspects of smart cities including main indicators for each sub-index (adapted from [21,22]).

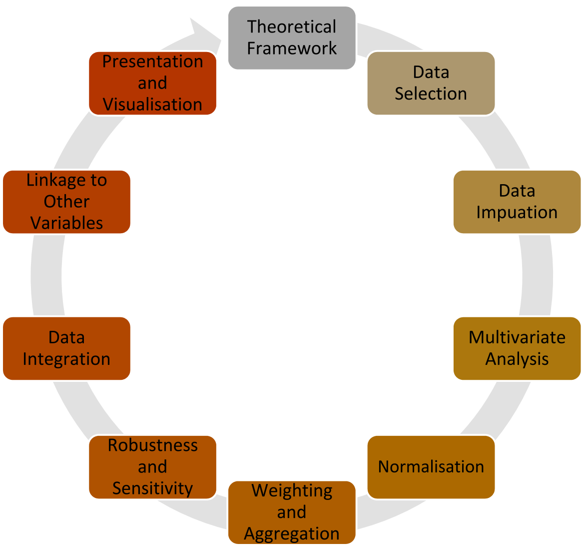

Fig. 2. Ten guiding principles to construct a composite indicator scheme.

Four performance indicators inform each domain and they are used to reflect the valuation of the respective domain. Indicators are selected on the basis of their relevance, analytical soundness, timeliness and data availability. The following functions highlight the functions used to obtain the smart city index:

$$SCI_{(\beta,\omega)} = \prod_{i=n}^{m} \beta_i^{\omega_i} \tag{1a}$$

$$Smart\ City\ Index = \gamma_{SEnv}{}^{\omega_{Env}} \times \gamma_{SEco}{}^{\omega_{Eco}} \times \gamma_{SSoc}{}^{\omega_{Soc}} \times \gamma_{SGov}{}^{\omega_{Gov}} \times \gamma_{SEn}{}^{\omega_{En}} \times \gamma_{Infra}{}^{\omega_{Infra}} \tag{1b}$$

$$\times \gamma_{STrans}{}^{\omega_{Trans}} \times \gamma_{PResil}{}^{\omega_{PResil}}$$

Since this paper primarily focuses on the economic and environmental aspects, these domains are explored in more depth. The economy is a critical domain in a city and for any smart city model to materialize, this domain is of great significance. The economy flourishes and grows in spirit of all the automation and the system optimizations that take place throughout all domains. This allows for more opportunities, innovative ideas and entrepreneurial platforms to grow and expand. Imports and exports as well as the GDP per capital are indicators that help assess this domain. The economic aspect is then evaluated as follows:

$$\gamma_{SEco} = \beta_{GDP}{}^{\omega_{GDP}} \times \beta_{RD}{}^{\omega_{RD}} \times \beta_{UR}{}^{\omega_{UR}} \times \beta_{GC}{}^{\omega_{GC}} \tag{2}$$

where β represents the dimensionless normalzied value for the respective indicator and ω represents the weight associated with each indicator. This sub-index is composed of GDP per capita β_{GDP} , research and development β_{RD}, unemployment rate β_{UR}, and the Gini coefficient β_{GC}.

The gross domestic product (GDP) per capita serves as a robust indicator of how effective an economy is for a particular population. Essentially, it represents the monetary value of all goods and services produced within a city or country during a specific period. Its value lies in providing an economic snapshot that can be used to evaluate the size and growth rate of an economy, making it a key tool for policymakers, investors, and businesses in making strategic decisions. Measured as GDP per person in the national population, cities with higher GDP per capita tend to enjoy a higher standard of living and greater income satisfaction. To promote sustainable economic growth and a prosperous GDP per capita, smart city must prioritize this indicator. Thus, the function used to assess it is:

$$\beta_{GDP} = \frac{\delta_{GDP_0}}{\delta_{GDP}} \tag{3}$$

where δ_{GDP} is the GDP per capita for a given city, compared to the reference state GDP per capita, which could be the regional, national GDP per capita.

Research and development activities play a critical role in the successes of an economy. In fact, it is a crucial component of innovation and a key factor in developing new competitive and alternative advantage. Furthermore, the whole concept of smart cities stemmed from research and development. Many of the technologies and services that have become deeply rooted and integrated in mankind's lifestyles such as cellular phones, internet, or computers are as a result of research and development. The transformation of technology to produce novel products, processes and services is essential in a smart city that thrives on continuous growth. Therefore, cities that have higher expenditure in this sector have higher potential to innovate and create; thus having a smart economy and a smarter city index. Thus, the function used to assess this indicator is:

$$\beta_{RD} = \frac{\sum R\&D\ Expenditure}{\sum GDP} \tag{4}$$

Innovation is considered a key indicator for smart cities. As new technologies constantly emerge to optimize and enhance current practices, this indicator covers a wide range of sectors. Commercial breakthrough and groundbreaking research are carried out by universities, public institutions and the commercial sector. A smart city is the one that capitalizes on all of these stakeholders to ensure the city prospers. This indicator assesses the level of creativity and innovatively that a city enjoins. This is assessed by evaluating the bond between academic institutions and industry. The surveys are designed to answer to what extent do businesses and universities collaborate on research and development. The following function is the employed:

$$\beta_{IC} = \frac{\delta_{IC}}{\delta_{IC_0}} \tag{5}$$

where δ_{IC} is the answer to the survey question: In the country, to what extent do businesses and universities collaborate on research and development (R&D)? [1 = do not collaborate at all; 7 = collaborate extensively] and δ_{IC_0} is the total for the answer. In summary, β_{IC} is the average answer to the survey question.

Note that unemployment is recognized as a disastrous trend for a city. In fact, the cities that have higher unemployment rates have shrinking economies and therefore declining cities. On the contrary, cities with lower unemployment rates have growing economies and smarter cities. It is critical for a city to present its citizens with various types of opportunities, allowing for their skill and talent to be captured in the best of ways. Furthermore, this indicator can be used to offset unemployment rate, discussed earlier. Job creation is essential to ignite shared and sustainable economic growth. The job creation leads to lower interest rates and more spending on public works and infrastructure enhancement. Furthermore, cities that create jobs and provide opportunities for career growth to its citizens, keep them engaged, motivated and productive, thus resulting in a smarter society. This indicator is apparently measured by the following function:

$$\beta_{UR} = \frac{\sum UR}{\sum LF} \tag{6}$$

where $\sum UR$ is the total number of unemployed perons compared to $\sum LF$, which is the total labour force including those who work and those who don't.

The Gini coefficient indicator is assessed by evaluating applied tariff rate on products in addition to the intensity of local market competition. Local market competition is assessed through a survey [1 = not intense at all; 7 = extremely intense]. Furthermore, the domestic market scale is evaluated as measured by the GDP. The domestic market size is measured by gross domestic product (GDP) based on the purchasing-power-parity (PPP) valuation of country GDP, in current international dollars (billions). The following function summarizes the evaluation method for this indicator:

$$\beta_{GC} = \delta_{AT} + \delta_{LMC} + \delta_{DMS} \tag{7}$$

where δ_{AT} is the rate of applied tarrifs (%), δ_{LMC} represents the average answer to the survey, and δ_{DMS} is the domestic market scale in (billions $ GDP).

Note that the environmental sustainability is recognized as a critical consideration in the conceptualization and implementation of smart city initiatives. As highlighted in the introductory section, the anticipated growth in the global population and the associated increase in carbon emissions underscore the urgent need for smart city solutions that prioritize environmental conservation and mitigation. The subsequent section outlines the evaluation framework adopted for assessing the environmental performance of the proposed smart city model as follows:

$$\gamma_{SEnv} = \beta_{AQ}{}^{\omega_{AQ}} \times \beta_{CC}{}^{\omega_{CC}} \times \beta_{WM}{}^{\omega_{WM}} \times \beta_{BH}{}^{\omega_{BH}} \tag{8}$$

where β represents the dimensionless normalzied value for the respective indicator and ω represents the weight associated with each indicator. This sub-index is composed of air quality β_{AQ} , climate change and GHG emissions β_{CC}, waste management β_{WM}, and biodiversity and habitat β_{BH}.

Ensuring high air quality and minimizing pollution is considered a crucial aspect of smart environments, as air pollution has emerged as a significant public health concern, with poor air quality linked to premature deaths. Air quality is assessed by measuring concentrations of various pollutants, including but not limited to greenhouse gases (GHGs), $PM_{2.5}$, O_3, NO_2, SO_2, CO, and total reduced sulfur compounds (TRS), and comparing them to established air quality objectives and criteria. GHGs, which are the primary pollutants driving climate change, are of particular importance in assessing this sub-index. Ideally, a smart city should have environmentally-benign processes and operations that result in a pollutant-free environment. GHGs, including water vapor, CO_2, CH_4, and N_2O, absorb and emit radiant energy, and their rapid increase since the industrial revolution has contributed significantly to global warming. With the advent of smart cities, there is an opportunity to regulate and control GHG emissions to minimize harm to the environment. This indicator is computed by evaluating the GHG emissions per capita for a selected city and comparing it to the GHG emissions per capita in a reference state, which may be the surrounding region, provincial state, country, or continent. In Canada, the Environmental Protection Agency sets acceptable levels for air quality at 12–13 μg/m^3. The following function summarizes the evaluation method for this indicator:

$$\beta_{AQ} = \frac{\delta_{GHG}}{\delta_{GHG_0}} \tag{9}$$

The GHG emissions per capita (kt CO_2eq per capita) of a city, denoted as δ_{GHG}, are compared to a reference state, δ_{GHG_0} using the following function to obtain a dimensionless number that can be incorporated into the model. Additionally, in evaluating this indicator, the percentage or ratio of air and environmental protection measures implemented by various industries can also be taken into account. The specific data points employed in assessing this indicator are depicted in Table 1.

Table 1
The parameters considered to assess the air quality indicator.

Parameters	Unit
Total CO_2 Emissions	kt CO_2eq/B$
CO_2 Emissions - Power Sector	g CO_2/kWh
Methane	kt CO_2eq/B$
Nitrous Oxide	kt CO_2eq/B$
Black Carbon	kt CO_2eq/B$
Household solid fuels	*Daily Rate*
$PM_{2.5}$ exposure	μg/m^3
$PM_{2.5}$ exceedance	*% Population*

The water quality indicator encompasses water quality. A smart environment ensures that water remediation and management measures are incorporated in the overall city operation. Water recycling is also considered in this indicator. Reusing treated wastewater for beneficial agricultural and landscape irrigation or industrial processes enhances a smart environment concept. Furthermore, water recycling and effective management allows the city to have sufficient water resources for its demand, decreasing the diversion of water from sensitive ecosystems and preventing pollution. The following function summarizes the evaluation method for this indicator:

$$\beta_{WQ} = \frac{\delta_{WQ}}{\delta_{WQ_0}} \tag{10}$$

where δ_{WQ} denotes the water conductivity level in Siemens per meter [S/m]. conductivity of substances is an indicator of water quality. In fact, conductivity affects the salinity and total dissolved solids (TDS) content, thus affecting the concentration of oxygen levels in the water. This is compared to a reference state δ_{WQ_0}, which is considered the optimal value. Moreover, percentages indicating improvements in this sector or percentage of wastewater treatment (%) can also be considered for this indicator.

The management of waste is crucial in promoting environmental sustainability in a smart city. Waste may be generated from various sources such as residential, commercial, institutional, industrial, and municipal activities, and it may be either hazardous or non-hazardous. Improper disposal of waste can have negative environmental impacts such as soil and water pollution, and methane emissions from landfills contribute to global warming. This indicator assesses the effectiveness of waste management by measuring the percentage of resources conserved through recycling. The indicator can also be evaluated by comparing the amount of local waste disposal to a reference state and is computed as follows:

$$\beta_{WM} = \frac{\delta_{WM}}{\delta_{WM_0}} \tag{11}$$

Here, δ_{WM} represents the amount of waste generated by all sectors within a city, compared to the waste generated in a reference state, δ_{WM_0}. Additionally, the recycling rate, expressed as the percentage of waste being recycled in tonnes per day per year (tonnes/day/yr), can be used to assess this indicator. Alternatively, the waste generated can be divided by the GDP to obtain the recycling rate (tonnes/B$).

This indicator pertains to the safeguarding of biodiversity and natural habitats. Many ecosystems are experiencing significant changes, leading to a decline in biodiversity. Some species are becoming vulnerable, while others face the risk of extinction. The granular-level data points used for this indicator are outlined in the Convention on Biological Diversity's "Aichi Targets," which is a collection of internationally agreed-upon objectives for ecosystem management and conservation. These data points include marine protected areas, national and global terrestrial biome protection, species protection index, protected area representativeness, and species habitat index. Turnover rates, which express the ratio of the number of species in a system to their outflow rate, are also considered. This relationship can be expressed using the following function:

$$\beta_{ET} = \frac{\delta_{ET}}{\dot{\delta}_{OF}} \tag{12}$$

where δ_{ET} represents the quantity of species within a specific ecosystem within a city with respect to their outflow rates $\dot{\delta}_{OF}$, which is measured at (species/year). Table 2 shows these data points in further detail with their respective units.

Therefore, the quantity of species is assessed using the following function:

$$\delta_{ET} = \delta_{MPA} + \delta_{TBP} + \delta_{SPI} + \delta_{PARI} + \delta_{SHI} \tag{13}$$

where δ_{MPA} is the marine protected area assessed through the percentage of exclusive economic zone, δ_{TBP} is the terrestial biome protection, which is assessed through the percentage of biomes, δ_{SPI} is the species protection index, evaluated by Ref. [20] along with δ_{PARI} is the protected area representativeness index and δ_{SHI} is the species habitat index, both evaluated in the Environmental Performance Index aforementioned.

This indicator evaluates a city's ecological sustainability by analyzing three specific data points, which include the GDP per unit of energy use, the environmental performance index, and the number of certificates of conformity with standard ISO 14001 on environmental management systems issued. The environmental performance index is a ranking of 180 countries on 24 performance indicators across ten issue categories related to environmental health and ecosystem vitality. This index provides a measure at a national

Table 2
The parameters considered to assess the ecosystem turnover rate.

Parameter	Unit
Marine protected area	% of EEZ
Terrestrial biome protection - national weights	% of biomes (capped)
Terrestrial biome protection - global weights	% of biomes (capped)
Species protection index	Dimensionless
Protected area representativeness index	Dimensionless
Species habitat index	Dimensionless

scale of how close countries are to achieving established environmental policy goals, and serves as a scorecard highlighting leaders and laggards in environmental performance. The index ranges from 0 to 100, with a higher score indicating better performance. The following function summarizes the evaluation method for this indicator:

$$\beta_S = \delta_{GDPE} + \delta_{EP} + \delta_{EC} \tag{14}$$

where δ_{GDPE} is the GDP per unit of energy use for a city ($ per kg of oil equivalent), δ_{EP} is the environmental performance index, which is dimensionless, and δ_{EC} is the level of environmental conformorance (number of issued certifications per billion $ GDP).

The first step in creating a composite indicator involves developing a theoretical framework, which provides a foundation for selecting and combining variables based on their fitness for the intended purpose. Experts and stakeholders are often consulted during this step, along with conducting a thorough literature review.

The process of selecting data for composite indicators is a crucial step that involves careful consideration of various factors, such as analytical soundness, specificity, measurability, attainability, realism, and temporal aspects. Additionally, data availability, coverage, and relevance to the phenomenon being measured are key considerations, and proxy variables may be used when necessary. Missing data is imputed, and measures are taken to ensure the reliability of each imputed value and to identify any outliers. The selection of indicators is based on their strengths and weaknesses, and the interrelationships between them are carefully examined to avoid any arbitrary choices.

To facilitate aggregation, data normalization is performed to scale the data points to a value between 0 and 1, as the indicators may have different units. The selection of weights is a value judgement that can significantly impact the composite indicator and overall results. Therefore, it is crucial to choose the appropriate weighting scheme that reflects the relative importance of each indicator and domain, while accounting for the objectives and priorities of the smart city model. This approach ensures that the composite indicator accurately reflects the underlying construct and effectively captures the multidimensional nature of the smart city phenomenon.

Multi-criteria, geometric and arithmetic aggregatory methods can be used for composite indicators, and sensitivity analysis is conducted to assess the robustness of the composite indicators and the implications of methodological choices such as weighting and aggregation.

3. Results and discussion

In this section, we visualize the relationship between variables to gain a better understanding of their impacts on each other. This is particularly important when analyzing numerous variables at once, as plots and correlation coefficients can reveal patterns and reduce a large amount of data to a summarized subset of key relationships. Principal component analysis (PCA) is suitable for datasets with random variables that have standard deviations reflective of their relative significance in their application. PCA relies on both the correlations between random variables and the standard deviations of those variables. When the standard deviation changes while the correlation remains the same, it results in a change in the principal components. Since the data was standardized, a principal component with a variance of 1 indicates that it accounts for variation equivalent to one of the original variables. Additionally, the sum of all variances equals the number of original variables (8 sub-indexes). The first two principal components explain almost 78% of the variance in the original eight variables.

Overall, the relationships between the 8 indexes are illustrated in Fig. 3, showing the degree of influence and correlation between each index. For instance, the environment index is more positively correlated with the society, energy, governance and infrastructure indexes. The eclipse circle shows the data distribution and how the values are spread out throughout the different cities in the model. Values that are better clustered show a stronger correlation, whereas values that are more spread out reflect more variation. On the other hand, the economy index is poorly correlated throughout all indexes, other than the transportation index. The 25%, 50% and 75% averages refer to the values above the average value in each index. For instance, the 25% average of the economy index means to 25% increase from the average economy index value as illustrated in Fig. 4.

Thirty-two axes are aggregated in Fig. 5 using the principal component analysis to have a better visual illustration of the performance of the indicators relative to each other. Similar to the index biplot, the clusters remain intact, however the values are a little bit more spread apart than the index values. The first component represents approximately 45% of the variation whereas the second component accounts for only 11% of the indicator variations. The biplot represents 56% of the original variation in the dataset. Each point on the biplot represents a city and each axis represents a performance indicator. The distance between points reflects the degree of similarity between them. Therefore, cities in close approximation to each other have similar profiles, whereas cities that are far from each other have dissimilar profiles.

Using multi-criteria decision making (MCDA), the indicator values are summed to compose the unweighted index value γ. This value undergoes four different weighting schemes, through which each index has the opportunity to be weighed at 7%, 13% and the maximum of 22%. The four weighing schemes proposed in this model are described in detail in Fig. 6.

The analysis of interrelationships between the environmental index and other domains reveals that the environment index has a strong positive correlation with the infrastructure index, followed by the energy and governance indexes. In contrast, it exhibits weak associations with the economy, transportation, and society indexes. It is noteworthy that the environment index has the highest correlation with the smart health index, suggesting that an environmentally sustainable city is likely to have a positive impact on the health and well-being of its citizens. These findings underscore the importance of promoting integrated and multidimensional approaches in designing smart city initiatives that prioritize environmental sustainability while considering the interrelationships between different domains.

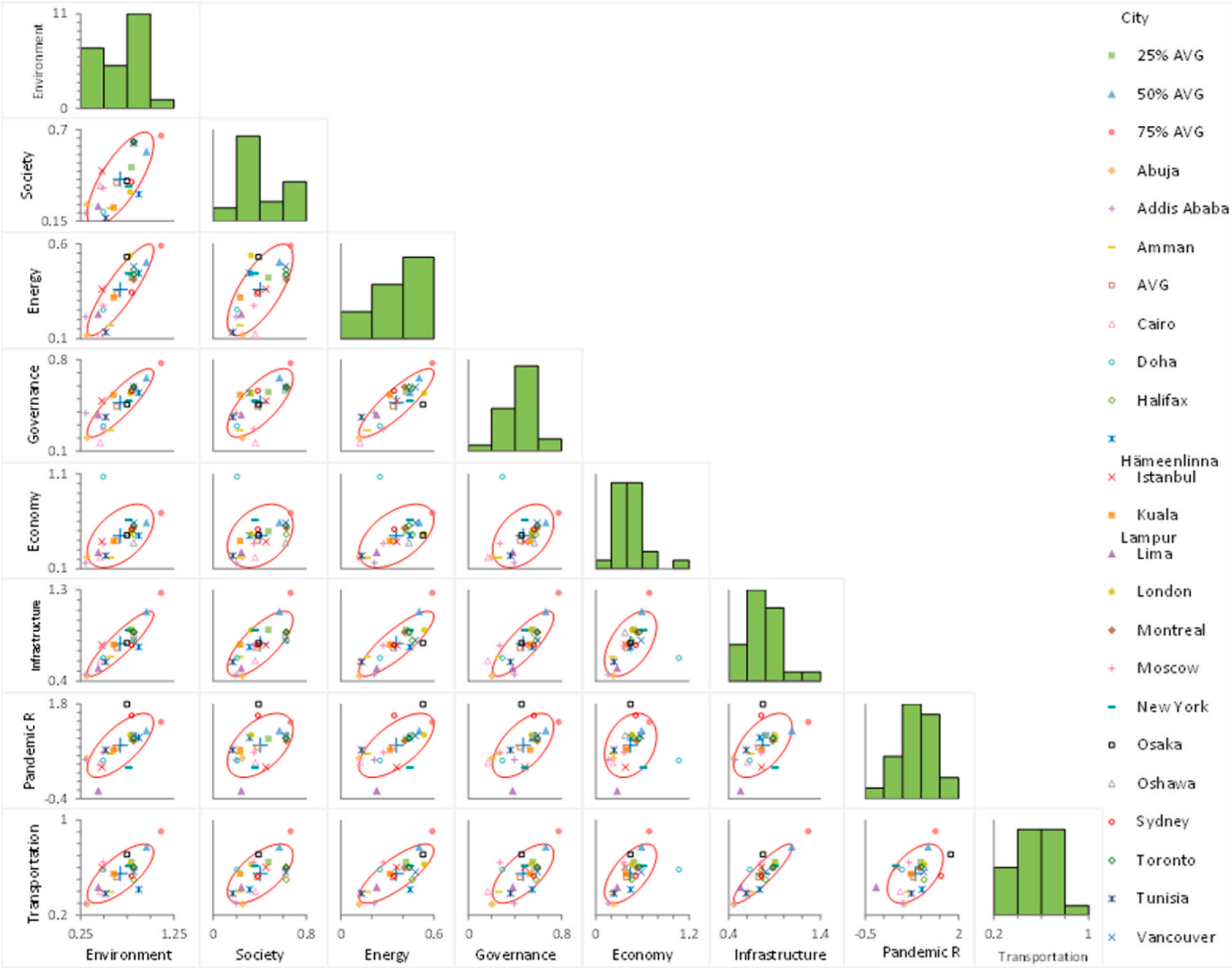

Fig. 3. A correlation of the eight indexes and their relationship and impact on each other.

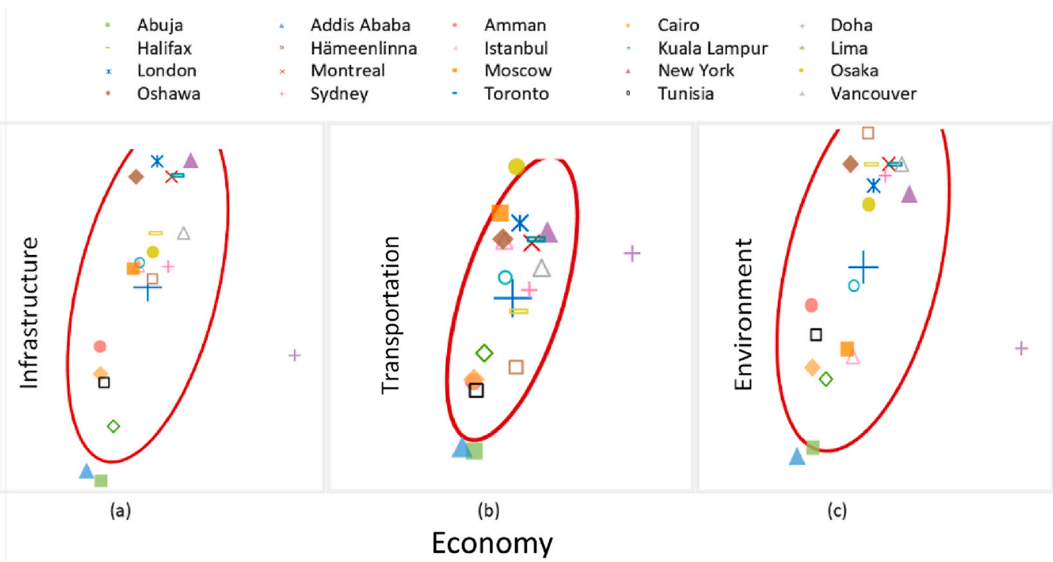

Fig. 4. A correlation of the economy index and other related indexes.

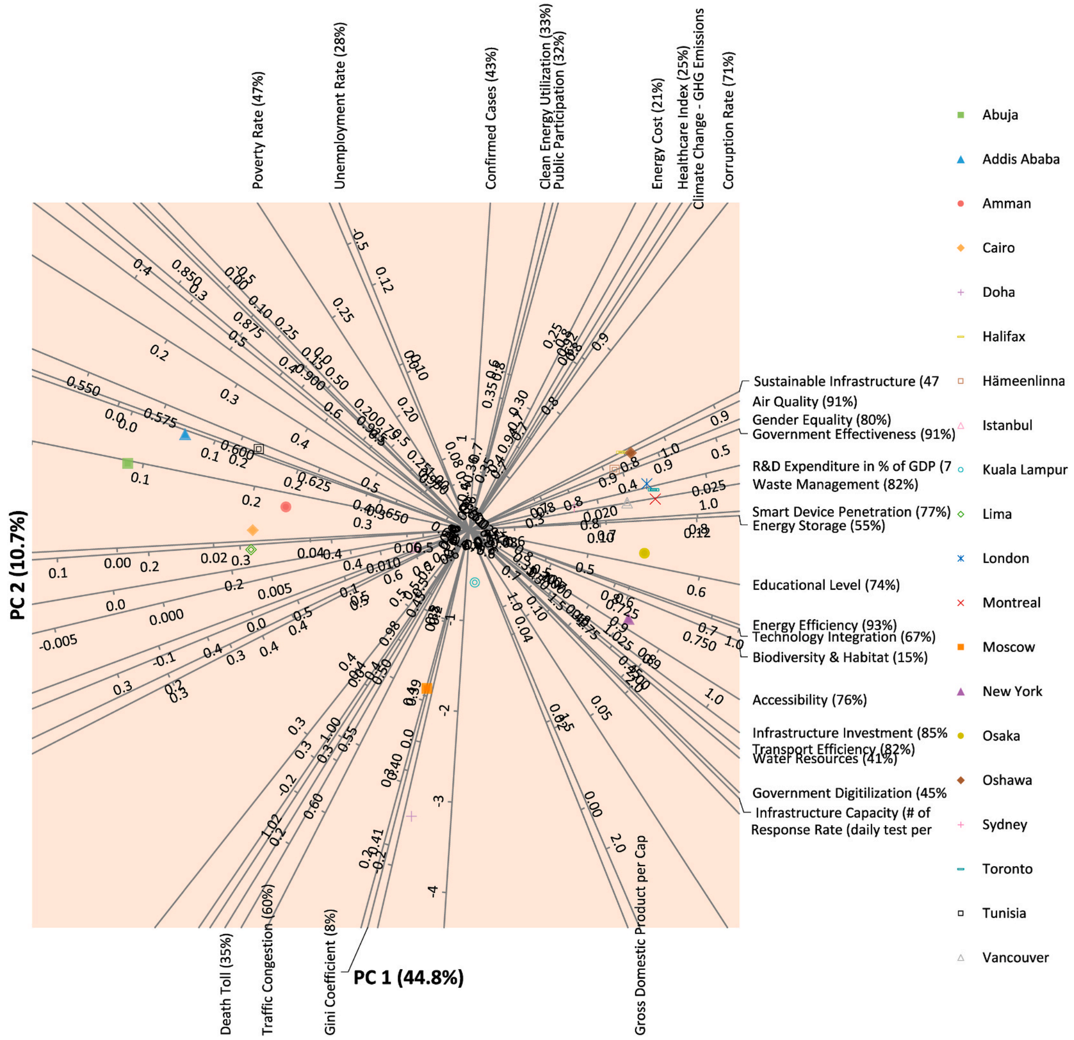

Fig. 5. Principal component analysis biplot aggregating all performance indicators.

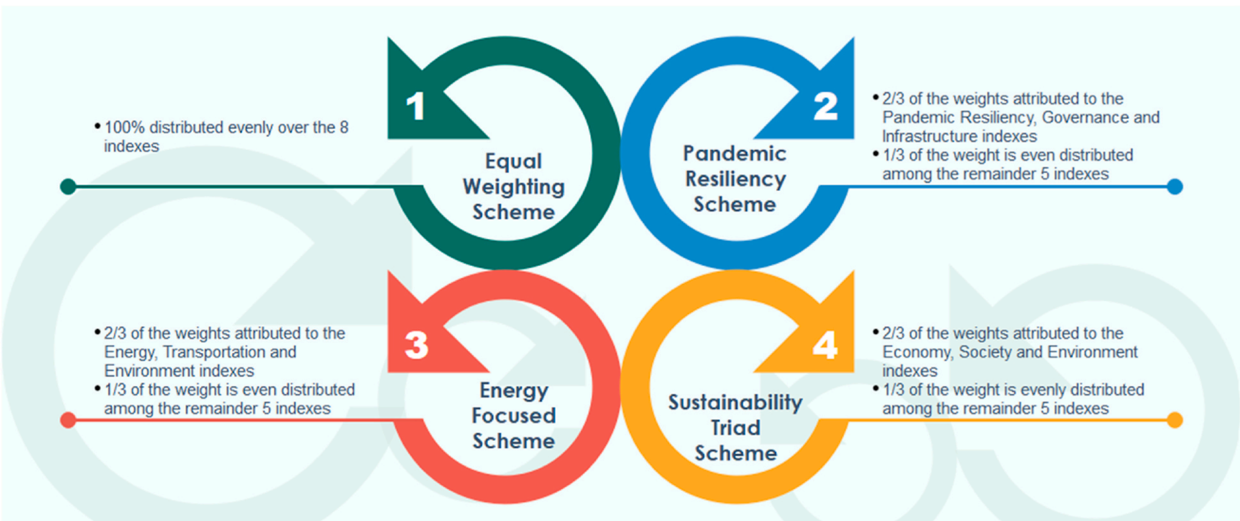

Fig. 6. Weighting schemes used in this study.

In the model development section, it was discussed that weighting and aggregation are essential in computing a composite model. To account for the multi-disciplinary nature and diverse indicators used in this study, a multi-criterial decision analysis and principal component analysis were employed. To visualize the relationships between variables, a two-dimensional monoplot of the coefficients of the first two principal components was used. In the monoplot, vectors representing the original variables point away from the origin, with the angle between the vectors indicating the degree of correlation between the variables. A small angle suggests a positive correlation, while a 90-degree angle indicates no correlation. An angle of 180° indicates a negative correlation.

The clustering analysis shows that the cities can be categorized into four distinct clusters based on their similarities in portfolio. The first cluster includes Abuja, Addis Ababa, Tunisia, Amman, Cairo and Lima, which are located in close proximity to each other on the plot. The second cluster, composed of Moscow, Istanbul, and Kuala Lampur, is situated in the middle of the plot. The third cluster consists of Western cities such as Canadian cities, London, Osaka, Sydney and Hameenlinna. The final cluster comprises outliers such as New York and Doha. New York stands out as an outlier due to its superior infrastructure, economy, and transportation values. On the other hand, Doha's economic index value of 107% is more than double the average, which can be attributed to its small population size and significant GDP per capita.

According to the results of the correlation analysis, the economy index exhibits a strong positive association with the infrastructure and energy indexes, with a moderate relationship observed between the economy index and the transportation, governance, and environment indexes. Conversely, a weak correlation is evident between the economy index and the health and society indexes. The findings, presented in Fig. 4, are derived from the granular level data collected for the 20 cities, which were computed to determine the total index value in their respective domains.

Notably, the infrastructure index displays the highest Spearman's Rs value with the economy index, indicating a significant correlation between the two variables. Specifically, an increase in the value of the smart infrastructure index corresponds to a rise in the smart economy index value, thereby highlighting the crucial role of smart infrastructure in driving economic growth.

The first scheme is the equal weighting scheme, where all eight indexes are given the same weight and degree of significance, when calculating the final Smart City Index score. The second scheme highlights the traditional sustainability pillars of economic, societal, and environmental sustainability. Thus, these three indexes combined account for two thirds of the weights, whilst the last third is distributed evenly among the remainder five indexes, leaving each index to be rated at 7%. Similarly, the third scheme takes an energy focused approach by giving two thirds of the weight to the energy, environment, and transportation indexes, leaving the remainder five indexes with the last third of the weight, evenly distributed among them. Lastly, the smart health focused scheme gives two thirds of the weight to the smart health, infrastructure, and governance indexes, leaving the last third evenly distributed among the remainder indexes in the model. Using this methodology, data points for indicators were collected from 20 cities worldwide. The selection of these cities was based on the availability and quality of data, with representation from all continents and inclusion of both developed and developing countries. Fig. 7 displays the map of the selected cities. Outliers that exceeded the considered range were removed to ensure uniformity and consistency. These outliers included the economic index of Doha. Three clusters of the environmental index are observed, with two below average and the third slightly above, ranging from 0.75 to 0.87.

Fig. 7. Twenty cities across the world explored in this study.

The governance index ratio is 0.44 and there is variation between cities, ranging from 0.17 to 0.59. Montreal has the highest ratio, while Cairo has the lowest. Disparity in the economy index is evident as clusters of cities can be grouped based on the results. The value of Doha of 1.72 was excluded because it is considered an outlier. This significantly high value stems from the substantial GDP that Doha enjoys with very minimal population, making the GDP per Capita indicator considerably high. New York, Toronto, and Vancouver scored more than 0.9 on this index. Smart health results also show considerable variation as some are performing very poorly with scores that are less than 0.2, while others are hitting the average, which is 0.45. After identifying Lima, Osaka, and Sydney as outliers, these cities were excluded from the averaging process. Based on an equal weighting scheme, Sydney achieved the highest Smart City Index (SCI) of 0.72, while Lima garnered the lowest SCI of 0.26. On the other hand, when applying the sustainability triad scheme, Toronto attained the highest SCI of 0.77, with Abuja obtaining the lowest SCI of 0.31. It is noteworthy that Toronto, Vancouver, and Montreal maintained their positions in the top five cities across all three schemes, namely equal weighting, sustainability triad, and energy focused. Furthermore, the energy focused scheme identified four Canadian cities, with Montreal ranking highest at 0.7, and Oshawa following closely at 0.67. The lowest in this scheme remains Lima with a SCI score of 0.27. From a smart health focused scheme, Sydney, Osaka, followed by Hämeenlinna score the highest with SCI scores of 0.81, 0.79, and 0.7 respectively. While the energy focused scheme resulted in the most conservative and pessimistic SCI for the cities, the smart health focused scheme resulted in the most optimistic SCI values. The biggest difference among the highest SCI scores between the different schemes is 0.11, whereas the biggest difference among the lowest SCI scores is 0.12.

The relationship between the government effectiveness ratio and the GDP per capita has been previously studied in the literature. Based on the model in this article, a clear exponential relationship is observed between the two indicators with a p value of less than 0.05, suggesting a strong causative correlation between the two indicators. Furthermore, cities with higher government effectiveness ratios tend to have higher GDP per capita. These findings are in line with [23], who developed a composite governance index and concluded that increases by one unit of the governance index results in 2% increase to the GDP per capita. Furthermore [24], also reported significant positive effect of the government effectiveness on economic growth, after analyzing 81 countries using the System Generalized Method of Moments. Lastly and most recently, Lee and Whitford also show a linear positive relationship between perceived government effectiveness and the GDP.

Sustainability traditionally revolves around the social, economic and environmental perspectives. Does a smart environment result in a smart economy? This is a critical question for both governments and societies alike. After all, economic growth is most sensible and has direct impacts on those stakeholders, whereas the environmental aspects are more long term and not physically experienced. Based on this model, environment has an exponential positive relationship with economy. In other words, increases in the smart environment index ratio, results in exponential increases to the smart economy index with p value lower than 0.05, indicating significance between the two indexes.

This is in line with the European Environment Agency who reported that our consumption and production systems are unsustainable. Similarly [25], suggested that while environmental impacts of economic growth may include pollution, global warming and disruption of environmental habitats, some forms of economic growth can mitigate that such as clean energy technology and renewables.

Furthermore, since the GDP per capita is considered one of the main and important indicators that enhance the smart economy index, a parametric assessment is conducted to show how enhancements to the GDP per capita impact the overall smart economy index. Fig. 8 shows the predicted smart economy indexes after 25% and 50% enhancement to the GDP per capita from the current

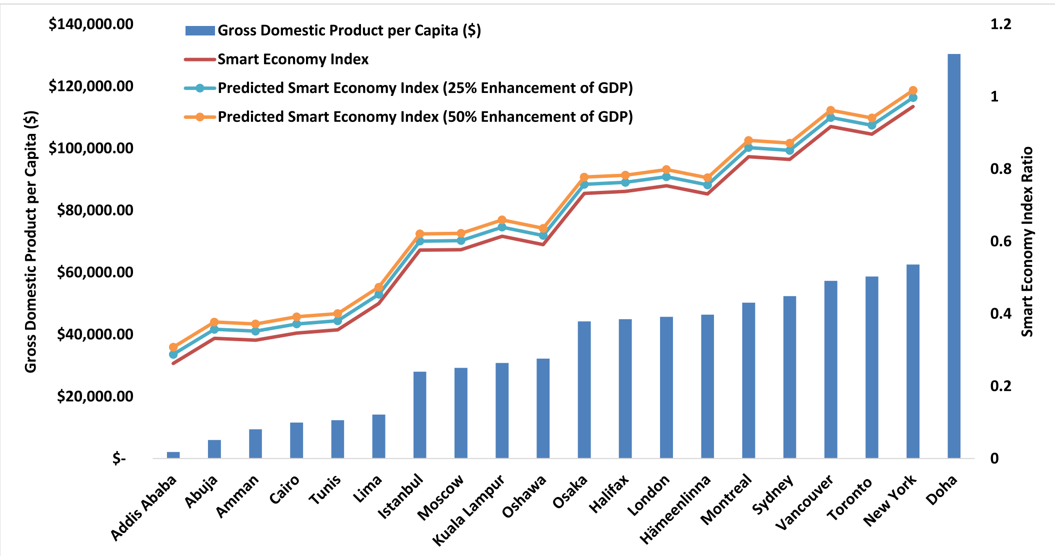

Fig. 8. Impact of GDP per capita on the overall economic index.

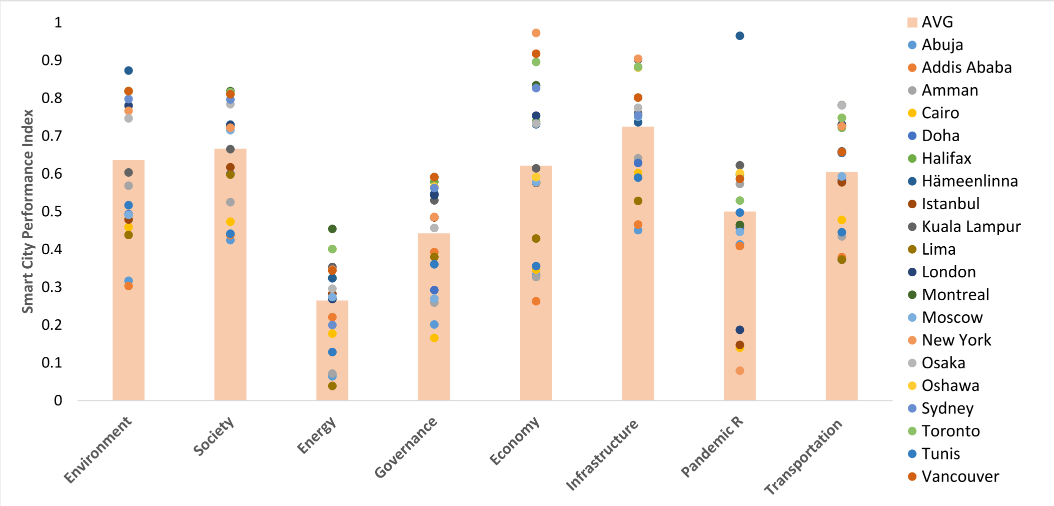

Fig. 9. Cities performance on various indexes along with the calculated average for each index.

values. It is important to note that for this model, considerable enhancements to the GDP per capita results in very modest increases in the overall smart economy index. This could be due to the impact of the other economic indicators such as percentage of expenditure on research and development. Finally, Fig. 9 shows the results of these cities against each unweighted index. According to the average results, the energy index has the lowest ratio, followed by governance and smart health. On the other hand, infrastructure has the highest ratio, followed by the environment, economy, and transportation indexes

For Doha, the Sustainability Triad scheme makes it the fourth highest, as it factors in its strongest suite, the economy index. However, equal weighting brings it to the 9th place with 0.619. The other schemes do not take the economy index into consideration, bringing Doha to 0.546 and 0.549 based on the Smart Health Focused and Energy Focused schemes, respectively.

An exponential relationship exists between the energy environment indexes. This is also proven as smarter energy index performance by utilizing more clean energy, enhancing energy storage and improving energy efficiency all contribute to lower GHG emissions, better air quality and waste management, consequently preserving of habitat. Fig. 10 illustrates the relationship between these two indexes.

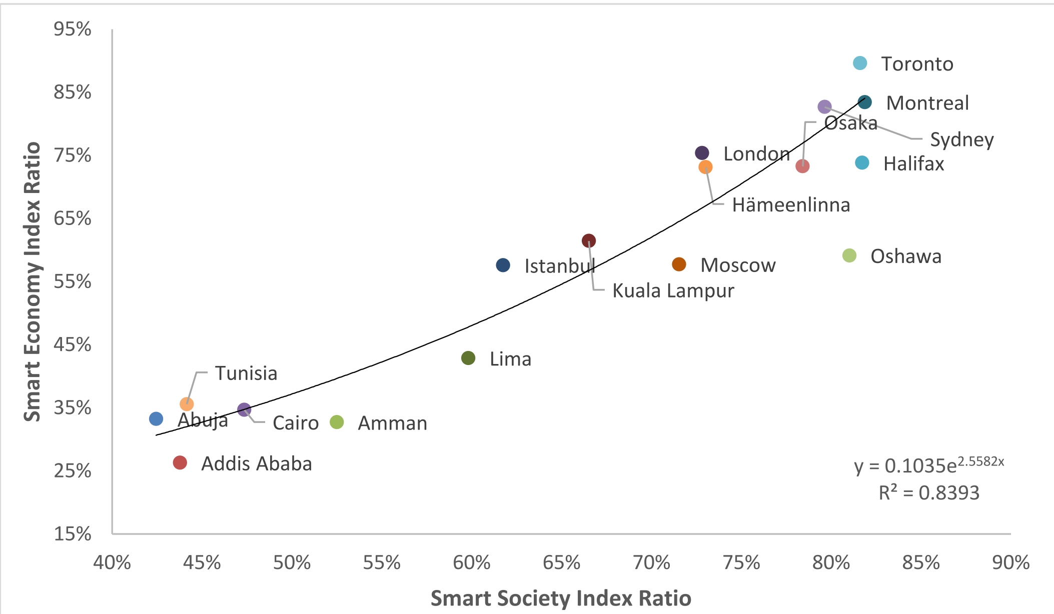

Fig. 10. Relationship between society and economy indexes.

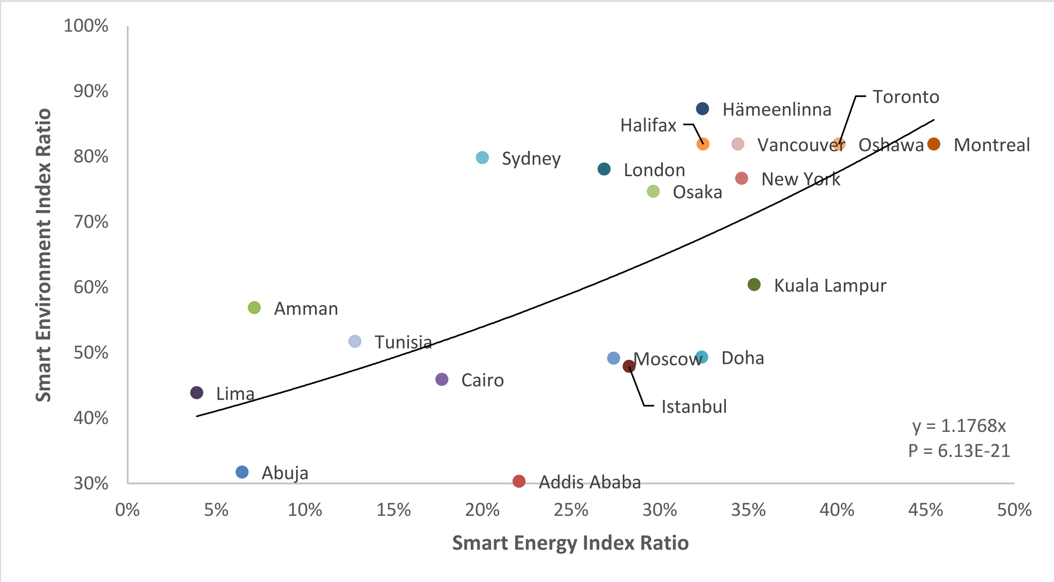

Fig. 11. Relationship between energy and environment indexes.

Another important domain is the infrastructure index. Does investment and enhancement in the energy index result in better and more resilient infrastructure? According to the results in this model, there is a significant positive linear relationship between the energy and infrastructure indexes, suggesting that higher energy index ratio is associated with higher infrastructure index ratio. This is clear as the p value is much less than 0.05, as illustrated in Fig. 11. Clean energy utilization and energy efficiency both correlate with the infrastructure's indicators of sustainable infrastructure and smart device penetration. Similarly, lower energy cost, allows for infrastructure investment to be enhanced. In fact, Fig. 11 shows the smart environment and its respective smart energy index for the different cities.

The average SCI is relatively remarkably similar among the four different weighting schemes, which reflects the accuracy and resiliency of the model. The Energy Focused scheme results in a more compacted results set with pessimistic results, whereas the Smart Health Focused scheme results in the most optimistic results for all cities except for the City of Lima.

4. Conclusions

This paper presents an innovative and expansive conceptual model for the development of smart cities, incorporating eight main domains and 32 performance indicators, synthesized via multi-criteria decision analysis (MCDA) to form a composite Smart City Index. The framework introduces a Smart Health factor to evaluate a city's pandemic response, such as COVID-19, while emphasizing socioeconomic transformations and innovations to enhance and promote sustainable economies. The model is applied to 20 selected cities worldwide, revealing Sydney, Osaka, Toronto, Montreal, and Vancouver as leading cities toward smart and innovative urbanism, scoring the highest among the 20 cities. The environment index ratio exhibits a tri-modal distribution, with two clusters below average and the last cluster slightly above average, ranging between 0.75 and 0.87. A clear positive correlation between the smart environment index ratio and the smart economy ratio is apparent across all 20 cities, with a p-value of less than 0.05. A strong correlation is observed between the society and economy indexes, with a noteworthy R value of 0.84. Additionally, the interdependence of the society, governance, and economy indexes suggests mutual influence and interaction. Notably, climate change and energy aspects can be significantly enhanced via the incorporation of clean energy, integrated and efficient energy systems, and various storage solutions. According to the equal weighting scheme, Sydney attains the highest SCI of 0.72, while Lima achieves the lowest SCI of 0.26.

Author contribution statement

Azzam Abu-Rayash: Conceptualization, Methodology, Formal analysis, Investigation, Data Curation, Writing-Original Draft.
Ibrahim Dincer: Conceptualization, Methodology, Writing-Review & Editing, Supervision, Project administration.

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Data availability statement

No specific data were used for the research described in the article.

Declaration of interest's statement

The authors declare no conflict of interest.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.heliyon.2023.e14347.

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