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Prioritizing Sustainable City Factors: A Generative AI-Driven Fermatean Fuzzy Prioritization Framework

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Abstract

Sustainable cities are vital for addressing global environmental and social challenges, yet evaluating their diverse sustainability aspects remains complex. Traditional Multi-Criteria Decision-Making (MCDM) methods often suffer from subjectivity, resource intensity, and cognitive burden due to reliance on small expert pools and pairwise comparisons. This study introduces an integrated framework to overcome these limitations by identifying and prioritizing key factors for urban sustainability evaluation. We employ BERTopic, a transformer-based topic modelling technique, to systematically extract 12 relevant factors from the academic literature. Instead of human experts, we leverage a state-of-the-art generative Artificial Intelligence (AI) model (Gemini 2.5 pro) with chain-of-thought reasoning to provide structured evaluations for these factors across different importance clusters. The inherent uncertainty in these AI-generated judgments is modelled using fermatean fuzzy sets. Finally, the factors are prioritized using the soft cluster rectangle method, eliminating the need for pairwise comparisons. Results indicate that pollution control, water management, and social equity are the highest-priority factors, followed by sustainable transportation, urban ecology, population health, and urban resilience. This study presents a more objective, scalable, and efficient data-driven approach to aid policymakers in strategic urban sustainability planning.

Keywords: Sustainable cities, Multi-criteria decision-making, Fermatean fuzzy, Generative artificial intelligence, Factor prioritization.

1 | Introduction

A sustainable city is a concept of urban development that encompasses various dimensions of self-sufficiency, including the environmental, social, and economic aspects. A "sustainable" city aims to create the smallest possible ecological footprint while ensuring a high quality of life for its residents. Environmentally, it

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emphasizes minimizing resource consumption, reducing greenhouse gas emissions, and promoting renewable energy and efficient public transport systems. Socially, a sustainable city strives for inclusivity, equity, and access to essential services such as healthcare, education, and housing. Economically, it encourages resilient local economies, green jobs, and innovation that align with sustainability goals. Overall, the concept reflects a holistic approach to urban planning [1], [2].

The human population is currently grappling with several significant issues. One of the most pressing among these is rapid population growth, particularly in developing nations. Rapid population growth places an immense pressure on already limited resources, contributing to the depletion of essential commodities such as water, food, and energy [3]. The strain on infrastructure and public services also intensifies, leading to overcrowded urban environments and inadequate healthcare systems. As a result, socio-economic disparities widen, and problems such as poverty, unemployment, and social unrest become more pronounced [4], [5]. Increased greenhouse gas emissions driven by industrialization, deforestation, and fossil fuel dependence are causing climate change, resulting in extreme weather events, sea-level rise, and ocean acidification [6], [7].

Pollution, including contaminated drinking water and air pollution, is a significant health and environmental issue [6]. The recent COVID-19 pandemic highlighted the vulnerability of global health systems and the potential for widespread disease outbreaks. It exposed structural weaknesses in healthcare infrastructure, global supply chains, and crisis preparedness, even in high-income countries [8], [9]. Despite the urgency to address these complex issues, there remains a persistent lack of consensus on how to address these problems, which often leads to ineffective or counterproductive policies [10].

Sustainable cities can play a crucial role in addressing these challenges through several strategies. They reduce their carbon footprint by implementing green technologies, promoting energy efficiency, and enhancing waste management systems [11], [12]. These cities aim to be inclusive, ensuring that all residents have access to essential services and opportunities, thereby reducing inequalities [3], [8]. Furthermore, they encourage participatory governance and community involvement in decision-making processes, which can lead to more effective and accepted solutions [13]. The concept of sustainable cities has gained popularity in the existing literature. However, some key research questions could be further addressed:

I. (RQ1) What are the key factors for evaluating the "sustainability" aspects of a city?

II. (RQ2) How should these factors be prioritized?

The literature review reveals that numerous studies have employed Multi-Criteria Decision-Making (MCDM) techniques to address a wide range of sustainability-related challenges. However, several limitations persist in the existing approaches. Most MCDM studies rely on manual literature reviews or Delphi-based methods to identify relevant factors, often depending on a small pool of human experts to determine the priorities of these factors. These methodologies are not only time-consuming and resource-intensive but also susceptible to subjective biases. The MDCM methods in the literature for eliciting criteria weights often involve pair-wise comparisons, which may cause cognitive fatigue to the expert giving the input data, thus resulting in inconsistent results. There is a pressing need for more structured, data-driven frameworks that can efficiently identify and prioritize sustainability factors holistically.

In response to these challenges, this study has the following steps:

I. Identification of factors: Instead of relying solely on manual reviews or expert elicitation, the study leverages transformer-based topic modelling, "BERTopic," to analyse the existing literature on sustainable cities [14]. This method helps automatically extract prevalent themes and concepts, which are then refined, grouped, and categorized into meaningful factors relevant to evaluating urban sustainability.

II. Data collection on the factors: Instead of relying on a limited number of human experts who are often biased, the data is collected from three state-of-the-art generative Artificial Intelligence (AI) based experts with chain-of-thought capabilities [15]. This data is then modelled using Fermatean fuzzy sets to capture uncertainties [16].

III. Factor prioritization: Finally, the factors are prioritized using the Supply Chain Resilience (SCR) method [17].

The rationale for selecting these particular approaches for developing a decision framework for prioritization of factors that can be used to evaluate the "sustainability" of a city is as follows:

I. BERTopic is an advanced topic modelling technique that utilizes transformer-based embeddings to generate semantically meaningful clusters of text [14]. This approach is particularly useful for analysing large volumes of literature and identifying nuanced patterns that may be missed by traditional topic modeling methods such as LDA. By applying BERTopic to a corpus of research articles on sustainable cities, the study ensures that the extracted factors are not only grounded in the literature but also reflective of recent trends and emergent themes in sustainability discourse. This data-driven and scalable method significantly reduces the dependence on manual review, making it more efficient and less prone to human bias.

II. Use of generative AI-based expert with chain-of-thought reasoning capabilities enables comprehensive and logically structured evaluations by simulating human-like reasoning. Compared to traditional human experts, this approach is faster, scalable, and draws from a vast and diverse knowledge base that these AI models were trained on. It avoids logistical constraints and common cognitive biases, offering more consistent and objective insights.

III. Fermatean fuzzy set is a q-rung orthopair fuzzy set with q=3 that is used to interpret uncertainty using two dimensions, i.e, preference/membership and non-preference/non-membership values [16]. Fermatean fuzzy sets provide a bigger decision space compared to the other earlier variants of q-rung orthopair fuzzy sets.

IV. The SCR method [17] is a recent MCDM technique that allows for an effective weight allocation for criteria based on different importance clusters, while preventing the need for pair-wise comparisons.

From the literature review, it is evident that the development of an integrated decision framework that uses topic modelling and elicits data from generative AI-based experts could significantly contribute to the body of literature. Such a framework not only advances methodological rigor but also holds practical value for urban policymakers, enabling more adaptive, scalable, and evidence-based planning strategies that can accelerate the global transition toward sustainable and resilient cities.

2 | Literature Review

In this section, the extant literature on MCDM for sustainable cities, use of AI for decision-making, topic modelling with BERTopic, Fermatean fuzzy sets, and the SCR method has been reviewed.

2.1 | Multi-Criteria Decision-Making for Sustainable Cities

MCDM has emerged as a widely adopted methodological framework for evaluating sustainability in urban contexts. Given the inherently multidimensional nature of urban sustainability encompassing interdependent economic, environmental, and social dimensions, MCDM techniques offer a structured approach to assign weights and prioritize diverse, and often conflicting, criteria. Urban policymakers and researchers have increasingly turned to MCDM models to support evidence-based decision-making in areas ranging from urban planning and green infrastructure to energy efficiency and social equity [18], [21].

Numerous MCDM frameworks have been developed and utilized in the extant literature to assess urban sustainability. For instance, Tahmasebi Birgani & Yazdandoost [22] have developed an adaptive MCDM framework that integrates AHP [23], Entropy [24], and TOPSIS [25] to evaluate "resilient-sustainable urban drainage management plans" and applied the framework on a case involving the urban drainage system of Tehran city. Han et al. [26] combined a modified Delphi method with the AHP to develop a framework that prioritizes sustainability indicators for addressing issues arising from "construction and demolition waste management". Jamali et al. [27] developed a framework that combined the Delphi method and GIS [28] with MCDM approaches, DEMATEL [29], and ANP [30] to select and evaluate factors affecting urban resilience.

MCDM methods have often been combined with fuzzy set variants to address uncertainty present in real-world problems, particularly those involving sustainability. For instance, Choudhury et al. [31] had used

Pythagorean fuzzy sets alongside Einstein weighted averaging operator-based MCDM to model a problem involving the selection of a sustainable urban drainage system for Agartala, the capital of Tripura, India [32].

Kutty et al. [33] utilized spherical fuzzy sets alongside AHP and EDAS for evaluating sustainability, urban resilience, and liveability performance of smart cities [34], [35]. Seker [36] developed an entropy-based MCDM framework that integrates interval-valued q-rung orthopair fuzzy for evaluating smart waste collection systems based on IoTs [37].

Seker et al. [38] integrated neutrosophic fuzzy with DEMATEL to evaluate factors needed for resilient and sustainable cities [39]. Krishankumar et al. [40] developed an MCDM framework that combines q-rung fuzzy with CRITIC and MACROS to evaluate zero-carbon measures for sustainable transportation solutions in smart cities. They applied it to a real-world case involving Coimbatore, India [41], [43]. The studies mentioned above have been summarized along with the gaps noticed in *Table 1* for ease of understanding.

Table 1. Description and gaps in the reviewed MCDM for sustainable cities studies.

Source	MCDM Model	Fuzzy Used	Pair-Wise Comparison Avoided	Used Topic Modelling for MCDM	Usage of AI/LLM-Expert
[22]	Entropy-AHP-TOPSIS	None	×	×	×
[26]	Delphi-AHP	None	×	×	×
[27]	Delphi-GIS-DEMATEL-ANP	None	×	×	×
[31]	Einstein-operator-based averaging	Pythagorean fuzzy	✓	×	×
[33]	AHP-EDAS	Spherical fuzzy	×	×	×
[38]	DEMATEL	Neutrosophic fuzzy	×	×	×
[40]	CRITIC-MACROS	q-Rung fuzzy	✓	×	×

2.2 | Methods Review

BERTopic was introduced by Grootendorst [14] as a novel topic modelling technique that uses transformer-based embeddings, such as those from BERT or similar models, combined with algorithms like HDBSCAN to generate coherent, semantically rich topics [44], [45]. Unlike traditional topic modelling approaches like LDA, which rely on word frequencies, BERTopic is capable of capturing deeper contextual relationships within text data [46]. BERTopic has been used widely by researchers to do topic modelling and thematic analysis for sustainability applications and urban planning. For instance, Kousis and Tjortjis [47] employed BERTopic to discover key aspects of a smart city. Das et al. [48] used BERTopic to investigate sustainable tourism themes in the extant literature. Similarly, Raman et al. [49] performed a thematic and topic analysis of green and sustainable AI research using BERTopic.

Fermatean fuzzy sets, proposed by Senapati and Yager [16], evolve from the generalized orthopair fuzzy sets by assigning q=3 [41]. This variant of generalized orthopair fuzzy sets offers a larger decision-making space and greater flexibility to model uncertainty compared to traditional fuzzy, intuitionistic fuzzy, or even Pythagorean fuzzy sets [32], [50]. The variant of generalized orthopair fuzzy sets makes them particularly advantageous when dealing with sustainability assessments, where ambiguity, vagueness, and hesitation are inherent to stakeholder judgments and data interpretations. The SCR method was proposed recently by Zakeri et al. [17], who saw the need for an MCDM method that elicits criteria weights without using pair-wise comparisons. The nature of data to be fed to the SCR method not only reduces cognitive load on decision-makers but also mitigates inconsistencies commonly observed in manual judgment-based methods.

2.3 | Use of Artificial Intelligence in Decision Making

AI has become increasingly integral to decision-making frameworks, especially in complex, multi-dimensional contexts like urban sustainability. AI-driven decision-making offers notable advantages, such as scalability, consistency, and the ability to process vast amounts of diverse information efficiently. Particularly, with the emergence of large-scale generative AI models with chain-of-thought reasoning capabilities, the AI models can now be used for structured expert elicitation [15]. Chain-of-thought utilizes step-by-step reasoning processes, leading to deeper and logically coherent responses compared to direct, answer-based querying.

In the decision-making domain, AI models have the potential to be used by researchers to aid in scenario analysis and prioritization tasks that were traditionally labour-intensive and subjective. Hackl et al. [51] conducted a study where OpenAI's GPT-4 was used to rate responses to tasks related to macroeconomics in higher education based on the content and style. Their study revealed a high interrater reliability metric for the rating given by GPT-4, indicating that it is capable of generating consistent ratings. Jia et al. [52] explored the applicability of LLMs in decision-support systems using a framework grounded in behavioural economics theories and found that the LLMs generally exhibit patterns such as risk aversion and loss aversion similar to humans. Wang and Wu [53] explored the idea of using ChatGPT model as multi-criteria decision maker and found that output given by ChatGPT model closely align with those of human experts. These studies suggest and validate the idea of using LLM model as an expert in giving data for MCDM problems.

3 | Methodology

In this section, the methodology of the study has been described.

3.1 | Preliminaries

Here, some mathematical concepts about Fermatian fuzzy sets have been discussed.

Definition 1 ([41]). For a given reference set R, the q-rung orthopair fuzzy set $QF = \{r, u_{qf}(r), v_{rf}(r) | r \in R\}$, the constraints on the membership degrees of QF are given by

$$0 \le u_{qf}(r), v_{rf}(r) \le 1. \quad (1)$$

$$0 \le u_{qf}(r)^q + v_{qf}(r)^q \le 1, q > 0, \quad (2)$$

where $u_{qf}(r)$, and $v_{qf}(r)$ represents the membership degree and non-membership degree of r, respectively.

Definition 2 ([16]). A Fermatean fuzzy set is a q-rung orthopair fuzzy set with $q = 3$. Therefore, for a Fermatean fuzzy set $F = \{r, u_f(r), v_f(r) | r \in R\}$, the constraint on the membership degrees of F is as follows:

$$0 \le u_f(r), v_f(r) \le 1. \quad (3)$$

$$0 \le u_f(r)^3 + v_f(r)^3 \le 1. \quad (4)$$

Definition 3 ([16]). The accuracy, score, and normalized functions on the Fermatean fuzzy set $F = \{r, u_f(r), v_f(r) | r \in R\}$ is given by

microcircuitry between the neurons; its activation function; and its approach to assigning weight to the connections, which can be either supervised or unsupervised. The artificial neuron found in recent years is

$$\text{Accuracy: } A(F_1) = u_f(r)^3 + v_f(r)^3. \quad (5)$$

$$\text{Score: } S(F_1) = u_f(r)^3 - v_f(r)^3. \quad (6)$$

$$\text{Normalized score: } NS(F_1) = \frac{S(F_1)+1}{2}. \quad (7)$$

3.2 | Topic Modelling

The initial step of this study involves identifying key factors relevant to sustainable cities directly from the extant literature. The identification of key factors is achieved through the application of BERTopic, a state-of-the-art topic modelling technique [14]. Abstracts of the articles related to sustainable cities are to be extracted from the Scopus database using the following query:

“TITLE ("sustainable city" OR "sustainable cities" OR "green city" OR "green cities" OR "eco-city" OR "eco-cities") AND (LIMIT-TO (DOCTYPE , "ar") OR LIMIT-TO (DOCTYPE , "re")) AND (LIMIT-TO (LANGUAGE , "English"))”

Once the corpus is assembled, it is to be modelled as a pandas dataframe in Python. The Python library bertopic is used with embedding model 'all-mpnet-base-v2', representation model KeyBERTInspired, vectorizer model CountVectorizer with English stop words removal enabled, and c-TF-IDF model set to ClassTfidfTransformer enabled with “reduce frequent words” and BM25-based weighting, to extract prominent topics and their associated keywords from the corpus [54][57]. These keywords provide an interpretable summary of each topic, based on which topics are manually reviewed and named to reflect the underlying themes in the data. During this manual review process, topics that are found to be irrelevant to the problem statement are systematically excluded, and topics that are too similar are merged together to ensure that only meaningful, distinct, and contextually appropriate topics are retained.

3.3 | Fermatean Fuzzy Integrated Supply Chain Resilience Method with Artificial Intelligence Expert

Once the topics are identified as factors for evaluating the “sustainability” aspects of a city, these are then to be prioritized using the SCR method. In the SCR method, the decision makers assign membership values for each factor to the clusters “Immaterial”, “Mediocre”, and “Vital”. These cluster membership values are then used to calculate the weights for the factors. In this study, data obtained from generative AI is modelled using Fermatean fuzzy sets and is then processed using the SCR method to arrive at a factor ranking. The steps to do these are as follows.

Step 1. Each of the finalized factors (Topics) derived from the topic modelling is to be framed into structured prompts designed to solicit evaluations from “Gemini 2.5 Pro preview 03-25,” a recent state-of-the-art chain-of-thought-based reasoning enabled generative AI model by Google.

I. The prompt template to be used for soliciting the membership values is: “Based on your understanding of sustainable cities and sustainability aspects of a city, how would you score the membership of <factor> to the cluster <cluster> on a scale of 0-1 (Use decimal values)”.

II. The prompt template to be used for soliciting the non-membership values is: “Based on your understanding of sustainable cities and sustainability aspects of a city, how would you score the non-membership of <factor> to the cluster <cluster> on a scale of 0-1 (Use decimal values)”.

It is to be noted that when soliciting data for membership values, the prompts for all factor-cluster combinations are given together as a single prompt; this is done to encourage the relative reasoning capabilities of the model. Similarly, a separate combined prompt is produced in order to solicit data for the non-membership values from the generative AI model.

Step 2. The membership values and non-membership values for each factor-cluster combination are to be interpreted as Fermatean fuzzy data. The normalized score values for each Fermatean fuzzy factor-cluster combination should be found using *Eq. (7)*.

Step 3. A decision matrix $X = [x_{ij}]_{3\times n}$ is to be formed using the normalized score values. Here, n is the number of topics/factors selected in the previous section, x_{ij} represents the normalized score value for the j^{th} factor on i^{th} cluster, and $i \in \{\alpha, \beta, \gamma\}$. The cluster α represents “Vital”, β represents “Mediocre”, γ represents “Immaterial”. The values of x_{ij} have to be in range $[L, H]$. In this study, $L = 0.01$ and $H = 0.99$, where L represents the lowest possible score to be processed, and where H represents the highest possible score to be processed. We also have a third variable, $M = 0.5$, where M represents the model-neutral value.

Step 4. The score decision matrix is to be converted to a fuzzy representation matrix as suggested by Zakeri et al. [17]. Let the fuzzy representation matrix be $FR = [f_{ij}]$. The value $f_{ij} = (l_{ij}, m_{ij}, h_{ij})$, where l_{ij} is the lower boundary, m_{ij} is the center, and h_{ij} is the upper boundary. The x_{ij} is converted to f_{ij} using *Eq. (8)* adapted from Zakeri et al. [17].

$$f_{ij} = \begin{cases} \left(x_{ij}, x_{ij}, \dfrac{H + x_{ij}}{2}\right) \text{if } x_{ij} \in [M, H], \\ \left(\dfrac{3H + M}{4}, H, H\right) \text{if} x_{ij} = H, \\ \left((M - L) - \dfrac{M^3}{3H}, M, \dfrac{3HL + M^2}{M}\right) \text{if } x_{ij} = M, \\ (L, L, L) \text{ if } x_{ij} = L, \\ \left(\dfrac{x_{ij}\left(x_{ij} + 2L + M\right)}{2}, x_{ij}, x_{ij}\right) \text{if } x_{ij} < M, \\ \left(\dfrac{3x_{ij} + M}{4}, x_{ij}, x_{ij}\right) \text{if } x_{ij} > M \text{ and } x_{ij} < \dfrac{M + H}{2}. \end{cases} \tag{8}$$

Step 5. The weights for clusters α, β, and γ are set to $\delta_\alpha = 0.6, \delta_\beta = 0.3$, and $\delta_\gamma = 0.1$. These weights were set such that a cluster with higher perceived information is assigned a higher weight and vice versa. It must also be noted that the sum of all cluster weights is equal to *Eq. (1)*. The weight values have been set arbitrarily following the example given by Zakeri et al. [17].

Step 6. The cumulative soft cluster rectangle area φ_j for each factor j is computed using *Eq. (9)*.

$$\varphi_j = 2\big(\delta_\alpha^2 l_{\alpha j} m_{\alpha j} + \delta_\alpha^2 l_{\alpha j} h_{\alpha j} + \delta_\alpha^2 m_{\alpha j} h_{\alpha j} + \delta_\beta^2 l_{\beta j} m_{\beta j} + \delta_\beta^2 l_{\beta j} h_{\beta j} + \delta_\beta^2 m_{\beta j} h_{\beta j} + \delta_\gamma^2 l_{\gamma j} m_{\gamma j} + \delta_\gamma^2 l_{\gamma j} h_{\gamma j} + \delta_\gamma^2 m_{\gamma j} h_{\gamma j}\big). \tag{9}$$

Step 7. The area φ_j is normalized to obtain the weights w_j for each factor j. These weights are then used to rank the factors. The normalization is done using *Eq. (10)*.

$$w_j = \frac{\varphi_j}{\sum_j \varphi_j}. \tag{10}$$

4 | Results

Following the methodology outlined in the previous section, information from 1448 research documents was extracted from the Scopus database; out of these 1448, only 1371 had complete abstracts. The abstracts of these 1371 research documents were fed to BERTopic for topic modelling. A total of 19 topics were extracted by the BERTopic, from which 12 factors were formed. *Table 2* describes the topics extracted and their related keywords, along with the actions taken (If any) and the factors identified for evaluating the sustainability aspects of a city. For each topic, the identified factor (If applicable) reflects a key aspect of urban sustainability, such as innovative city technologies or sustainable transportation, derived from cohesive and relevant keywords.

The 12 factors identified were prompted to generative AI as per *Step 1* from Section 3. *Table 3* shows the generative AI given ratings in a structured form. These values were converted to normalized score values as per *Steps 2* and *3* from Section 3 and were formed into a decision matrix to be fed to the SCR method. *Table 4* shows the normalized score values for each factor-cluster combination. It must be noted that the factor-cluster combination scores were converted to 0.01 for those values that were 0. The factor-cluster combination score was done as $L = 0.01$. The decision matrix is processed by the SCR method using *Steps 3-7* of Section 3, resulting in factor weights for the 12 factors. These factor weights are used to rank the factors. *Table 5* shows the SCR area mentioned in *Step 6* of Section 3, the factor weights, and the rank assigned to each factor.

Table 2. Topics extracted using BERTopic and their conversion to factors for evaluating the sustainability aspects of a city.

Topic	Action Taken (If any)	Factor Identified	Keywords
Topic 1	The keywords extracted are too broad	-	Sustainability, ecological, cities, environmental, sustainable, settlements, heritage, land, city, housing
Topic 2	-	Smart city technologies (F1)	Sustainability, urbanism, cities, sustainable, IoT, data, environmental, sensors, analytics, intelligent
Topic 3	-	Sustainable transportation and mobility (F2)	Transportation, vehicles, logistics, transport, commuting, walkability, vehicle, emissions, freight, traffic
Topic 4	-	Urban ecology and green spaces (F3)	Streetscape, urbanization, ecological, gardens, ecology, landscapes, garden, ecosystem, ecosystems, vegetation
Topic 5	-	Pollution control (F4)	Sustainability, pollution, climate, emissions, environmental, eco, economic, Vilnius, countries, competitiveness
Topic 6	Found to be not relevant to the (RQ1)	-	urbanization, shenzhen, city, yangzhou, governance, tianjin, zhuhai, towns, governments, eco
Topic 7	Found to be not directly relevant to the (RQ1)	-	agroecology, agriculture, agricultural, agroecological, floriculture, farmers, horticultural, farms, cultivation, gardens
Topic 8	-	Building envelope and thermal efficiency (F5)	thermal, roofs, solarcity, rooftop, roof, insulation, buildings, architecture, architectural, building
Topic 9	-	Water management (F6)	stormwater, wastewater, drainage, wetlands, rainwater, irrigation, runoff, groundwater, flood, freshwater
Topic 10	Found to be not relevant to the (RQ1)	-	sustainability, branding, environmental, tourism, brands, destinations, brand, tourist, tourists, affordability
Topic 11	Merged into F7	Renewable energy (F7)	turbines, solar, geothermal, kwh, turbine, desalination, renewable, biomass, hydrogen, inverter
Topic 12	Merged into F7	Renewable energy (F7)	renewable, climate, emissions, energy, turbine, energies, buildings, electricity, power, subsidies
Topic 13	-	Population health (F8)	streets, health, greenness, housing, populations, obesity, lifestyles, healthier, prevalence, transport
Topic 14	Found to be not directly relevant to the (RQ1)	-	interdisciplinarity, educating, university, education, universities, disciplines, geography, interdisciplinary, curriculum, teaching
Topic 15	-	Social equity (F9)	gentrification, urbanism, neighborhoods, greening, environmental, gardens, decolonizing, cities , segregation, suburbs
Topic 16	-	Waste management (F10)	landfill, waste, recycling, composting, compost, disposal, sewage, waste, biowaste, pyrolysis
Topic 17	Found to be not relevant to the (RQ1)		LSTM, lstms, predicting, predictive, prediction, convolutional, rmse, dataset, neural, accuracy
Topic 18	-	Urban climate and microclimates (F11)	urbanization, climate, climates, vegetation, microclimates, climatic, land, landsat, temperatures, temperature
Topic 19	-	Urban resilience (F12)	resilience, Katrina, flooding, flood, disasters, resilient, socioeconomic, pandemic, inundation, rainstorm

Table 3. "Gemini 2.5 pro preview 03-25" evaluations of the factors, collected and structured into a table.

Factor	Membership/Non-Membership	Vital	Mediocre	Immaterial
F1	Membership	0.3	0.7	0
	Non-membership	0.6	0.4	0.9
F2	Membership	0.9	0.1	0
	Non-membership	0.1	0.8	1
F3	Membership	0.9	0.1	0
	Non-membership	0.1	0.8	1
F4	Membership	0.95	0.05	0
	Non-membership	0.1	0.8	1
F5	Membership	0.8	0.2	0
	Non-membership	0.2	0.6	0.9
F6	Membership	0.95	0.05	0
	Non-membership	0	0.9	1
F7	Membership	0.9	0.1	0
	Non-membership	0	0.9	1
F8	Membership	0.9	0.1	0
	Non-membership	0.1	0.8	1
F9	Membership	0.95	0.05	0
	Non-membership	0	0.9	1
F10	Membership	0.8	0.2	0
	Non-membership	0.1	0.8	1
F11	Membership	0.7	0.3	0
	Non-membership	0.2	0.6	0.9
F12	Membership	0.9	0.1	0
	Non-membership	0.1	0.8	1

Table 4. Decision matrix with normalized score values to be used for the SCR method.

	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	F11	F12
Vital	0.406	0.864	0.864	0.928	0.752	0.929	0.865	0.864	0.929	0.756	0.668	0.864
Mediocre	0.640	0.245	0.245	0.244	0.396	0.136	0.136	0.245	0.136	0.248	0.406	0.245
Immaterial	0.136	0.010	0.010	0.010	0.136	0.010	0.010	0.010	0.010	0.010	0.136	0.010

Table 5. Ranking of the factors determined; results of the Fermatean fuzzy integrated SCR method with an AI expert.

Factors	SCR area	Factor weight	Rank
F1	0.220689	0.02388	8
F2	0.854903	0.092506	3
F3	0.854903	0.092506	3
F4	0.960569	0.103939	1
F5	0.702521	0.076017	5
F6	0.954697	0.103304	2
F7	0.848967	0.091863	4
F8	0.854903	0.092506	3
F9	0.954697	0.103304	2
F10	0.690011	0.074663	6
F11	0.489875	0.053007	7
F12	0.854903	0.092506	3

5 | Conlusion

This study proposed a novel MCDM framework integrating BERTopic-based factor identification, generative AI expert elicitation, Fermatean fuzzy sets for uncertainty modelling, and the SCR method for factor prioritization to evaluate the sustainability aspects of cities. The results presented in *Table 5* offer a prioritized list of factors derived through this structured, data-driven approach.

The top-ranked factor, pollution control (F4), highlights the critical importance of addressing air, water, and soil pollution in urban environments to achieve sustainability. Pollution control aligns with the pressing global challenges highlighted in the introduction, where pollution is identified as a significant health and environmental issue [6]. Following closely are water management (F6) and social equity (F9), ranked joint second. Efficient and sustainable water resource management is crucial given population growth and climate change pressures, while social equity is fundamental to the social dimension of sustainability, ensuring inclusivity and access to opportunities for all residents [58–61]. The high ranking of these factors suggests that foundational environmental health and social justice issues are perceived as paramount for urban sustainability.

Factors such as sustainable transportation and mobility (F2), Urban ecology and green spaces (F3), population health (F8), and urban resilience (F12) share the third rank. This cluster highlights the interconnectedness of environmental quality (Green spaces, reduced emissions from transport), public well-being (Health outcomes), and the city's ability to withstand shocks (Resilience). The importance attributed to these factors reflects the holistic view of sustainable cities encompassing environmental integrity, quality of life, and preparedness. Renewable Energy (F7) ranks fourth, indicating its significant role, yet perhaps perceived as slightly less critical than immediate pollution control or water management in this specific evaluation context. Building envelope and thermal efficiency (F5) and Waste management (F10) follow, ranking fifth and sixth, respectively. While they are essential components of resource efficiency and environmental management, they were ranked lower than the top-tier factors.

Interestingly, urban climate and microclimates (F11) and Smart city technologies (F1) received lower ranks (Seventh and eighth, respectively). The relatively lower ranking of smart city technologies might suggest that while technology can be an enabler, it is perceived as less fundamental than core environmental, social, and resource management aspects for achieving sustainability [62], [63]. This finding contrasts with some narratives that heavily emphasize technology but aligns with perspectives prioritizing foundational sustainability principles [64–66]. The lower rank for urban climate might indicate that while related to broader climate change (Addressed partially by F4, F7), its specific focus on microclimates was deemed less universally vital compared to immediate pollution or resource issues by the AI expert.

In addressing the research questions posed:

I. (RQ1) What are the key factors for evaluating the "sustainability" aspects of a city? This study identified 12 key factors through a systematic, literature-driven topic modelling approach using BERTopic (Table 2). These factors span environmental (e.g., F4, F6, F7, F10, F11), social (e.g., F8, F9, F12), and infrastructural/technological dimensions (e.g., F1, F2, F5).

II. (RQ2) How should these factors be prioritized? The study prioritized these factors using an integrated Fermatean Fuzzy SCR method informed by generative AI expert input, resulting in the ranking presented in Table 5. An integrated Fermatean Fuzzy SCR method provides a clear hierarchy, suggesting areas for focused attention by policymakers.

Methodologically, this study successfully demonstrated the integration of advanced techniques to overcome limitations of traditional MCDM approaches. BERTopic enabled efficient, data-grounded identification of factors from a large corpus, reducing reliance on potentially biased manual reviews. Using a generative AI model (Gemini 2.5 Pro) with chain-of-thought enabled reasoning provided scalable and structured expert input, avoiding the logistical and cognitive load issues associated with human expert panels. Fuzzy sets effectively captured the inherent uncertainty in the AI's judgments, offering a more nuanced representation than crisp values. The SCR method facilitated weight elicitation without requiring laborious pairwise comparisons, mitigating cognitive fatigue and potential inconsistency, aligning with the identified gap in the Literature (*Table 1*).

The findings have significant practical implications for urban planners and policymakers. The prioritized list of factors can guide strategic planning and resource allocation towards areas with the highest perceived impact on urban sustainability, such as pollution control, water management, and social equity. Furthermore, the proposed framework itself offers a replicable, scalable, and adaptable methodology for evaluating sustainability priorities in different urban contexts or as new challenges emerge.

Despite the methodological contributions, this study has several limitations:

I. BERTopic's performance can be sensitive to parameter choices (e.g., embedding model, clustering algorithm settings). While state-of-the-art techniques were used, the resulting topics still required manual interpretation, filtering, and merging, introducing a degree of subjectivity. The analysis was also limited to abstracts, potentially missing nuances present in full texts.

II. While generative AI offers scalability and consistency, it is not without drawbacks. The AI's knowledge is based on its training data, which may contain biases or be outdated. Its "understanding" lacks the lived experience and contextual depth of human experts. Although Chain-of-Thought prompting encourages structured reasoning, the AI's internal processes remain somewhat opaque (A "black box"). The results are also specific to the AI model used (Gemini 2.5 Pro); other models might yield different evaluations.

III. The SCR method relies on predefined cluster weights ($\delta_\alpha, \delta_\beta, \delta_\gamma$) and boundary parameters (L, M, H). The choice of these parameters (Set arbitrarily in this study based on the original SCR paper) can influence the final weights, and determining optimal values requires further investigation.

IV. The study provides a snapshot prioritization. Sustainability priorities can evolve due to changing environmental conditions, technological advancements, or societal values.

Building on this work, future research could explore several avenues:

I. Investigate the impact of different embedding models or clustering algorithms within BERTopic. Compare the outputs of various generative AI models (e.g., GPT-4, Claude 3) as experts. Explore adaptive or data-driven methods for setting SCR cluster weights and parameters.

II. Integrate input from human experts alongside AI experts, potentially using a consensus-building approach or assigning different weights based on expertise domains. Integrating input from human experts alongside AI experts could combine the breadth of AI knowledge with the depth of human experience.

III. Apply the framework to specific cities or regions, incorporating local data and stakeholder input to tailor the factor list and prioritization to the unique context.

IV. Develop longitudinal studies to track how sustainability priorities shift over time and how the framework can be adapted for dynamic decision-making.

V. Extend the framework to model the interrelationships and feedback loops between sustainability factors (e.g., using methods like DEMATEL or ANP, potentially adapted to use AI-driven relationship mapping to reduce pairwise comparison burden).

VI. Apply topic modelling to the full texts of relevant articles, rather than just abstracts, to potentially capture more detailed and nuanced factors.

VII. Compare the rankings generated by this framework with rankings derived from traditional expert panels or other established sustainability indices for validation purposes.

By addressing these limitations and exploring these future directions, research can further enhance the utility of integrated, AI-assisted MCDM frameworks for advancing sustainable urban development.

Data Availability

The data extracted from the Scopus database, the normalized score values of the decision matrix, and the Python Jupyter notebooks written for the BERTopic modelling and SCR method can be found in the following GitHub repository: https://github.com/regiusherder/Prioritizing-Factors-for-assessing-Sustainablity-of-Cities

Conflicts of Interest

The authors declare no conflict of interest.

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