Journal of Operations Intelligence

Journal homepage: www.jopi-journal.org
eISSN: 3009-4267

Fermatean Fuzzy TOPSIS Method and Its Application in Ranking Business Intelligence-Based Strategies in Smart City Context

Seyed Shabahang Majd[1], Alireza Maleki[2,*], Sepideh Basirat[3] , Amin Golkarfard[4]

1 MBA, College of Business & Public Management, University of La Verne, CA, USA
2 College of Management, University of Tehran, Tehran, Iran
3 Master of Business Administration, Department of Business Administration, University of the Potomac, Washington, DC 20005, USA
4 Civil and Environmental Engineering Department, Amirkabir University of Technology, Tehran, Iran

ARTICLE INFO

Article history:
Received 19 Sepetember 2024
Received in revised form 21 October 2024
Accepted 8 November 2024
Available online 11 November 2024

Keywords:
Smart City; Business Intelligence; Fermatean Fuzzy Set; TOPSIS; Decision Making.

ABSTRACT

With the expansion of smart cities, the use of business intelligence (BI) has emerged as a crucial tool for resource optimization, increasing efficiency, and improving the citizens' quality of life. BI enables companies to make better strategic decisions by analyzing vast amounts of urban data, helping them remain competitive in the dynamic smart city environment. This study utilizes content analysis and the Fermatean Fuzzy TOPSIS (FF-TOPSIS) method to rank the strategies based on business intelligence in the context of smart city. Initially, relevant criteria were identified through content analysis, and subsequently, five strategies were developed and ranked based on these criteria. The results revealed that the "Development of IOT-enabled smart networks (S2)" ranked highest, as it plays a significant role in optimizing resource management and enhancing urban service performance, thereby contributing greatly to the advancement of smart cities. "Process automation and the deployment of robotic systems (S5)" ranked second, as it enhances efficiency and reduces human errors. "Cloud platform integration for seamless access to data and services (S3)" also proved to be of considerable importance, ranking third, as it provides seamless access to data and services. " Artificial intelligence deployment for predictive analytics and process optimization (S4)" ranked fourth and was vital for predictive analytics and process optimization, while " Big data analytics for smart decision-making (S1)"—despite its importance—ranked fifth. Urban managers should prioritize the development of IOT networks to fully leverage their potential for resource management and efficiency gains. Following this, attention to process automation and AI integration can significantly enhance the quality of life for citizens and reduce urban costs.

* *Corresponding author.*
E-mail address: *alimalekiglobal@gmail.com*

https://doi.org/10.31181/jopi31202532

1. Introduction

The concept of Smart City (SC) first emerged in the 1990s, with a focus on leveraging information communication technology (ICT) to enhance infrastructure and upgrade networks. The widespread adoption of information technologies has also enabled cities to advance essential services related to safety, health, governance, and service delivery [1]. There is no widely accepted definition of a smart city [2,3]. Instead, various definitions exist in empirical literature, some of which are provided in Table 1. While certain definitions focus on leveraging information communication technology and modern infrastructure [4-6], others emphasize human capital and quality of life [7]. Due to the lack of a single comprehensive definition, the term SC is often used to describe a wide range of developmental aspects, including ICTs, education, equality, and overall sustainability [8].

A smart city demonstrates forward-thinking performance across six key areas: economy, people, governance, mobility, environment, and living. It is developed through a strategic blend of resources and actions, driven by proactive, independent, and informed citizens [9]. Smart cities offer extensive economic benefits, including fostering innovation, promoting entrepreneurship, creating new job opportunities, and improving the competitive position of urban centers. They also reduce costs for businesses and residents while enhancing public service efficiency, acting as a catalyst for economic growth [10,11]. By driving rapid development, smart cities contribute to GDP growth, boost employment rates, and attract foreign investments, key factors in revitalizing urban economies [12], [13].

Beyond economics, smart cities excel in managing resources through technology and innovation, implementing eco-friendly energy systems, and conserving resources like water. They improve citizens' quality of life by optimizing public services, traffic management, and waste handling [14-17]. Smart cities also impact regional and global landscapes by becoming hubs for economic innovation, attracting investments, and nurturing future enterprises. Their role in driving technological advancement and economic progress is essential in today’s rapidly evolving world [18-20].

Table 1
Alternative definitions of smart city

Publication	Definition
Marsal–Llacuna et al. [4]	Smart cities initiative seeks to improve urban performance by using data, information, and Information Technologies (IT) to provide more efficient services to citizens, to monitor and optimize existing infrastructure, to increase collaboration between different economic actors and to encourage innovative business models in both the private and public sectors.
Regalia et al. [5]	The vision of smart cities … unifying sensor networks, cyber–infrastructures, interoperability, and predictive analytics research for the purpose of improving the quality of life.
Estrada et al. [6]	Smart cities concept is based on the use of information and communication technologies … in order to face the problems of diverse metropolises, such as reducing energy consumption or the negative impact of the city on the environment, the concept of smart cities has gained notoriety.
Trencher [7]	Smart cities strategies … put people first and stresses technology as a tool to use predominantly in service of citizens.
Solanki et al. [21]	The term ‘smart city’ is given to a city that incorporates technology to make the lives of people living in the city better in terms of healthcare, transportation, urban governance, and waste management.
Nagy et al. [22]	Smart city … contribute to improving living standards, increasing urban competitiveness, and overcoming obstacles such as poverty, social exclusion or environmental problems.
Patel and Doshi [23]	A smart city is comprised of different viewpoints that incorporate residents, city authorities, nearby organizations and businesses and local gatherings.

Publication	Definition
Dashkevych & Portnov [2]	A smart city is a city that aims to achieve economic, environmental, and societal sustainability goals and improves residents' well-being.

Sensors form the backbone of smart city operations by collecting data and transmitting it for processing [24]. While cloud computing can be used for this purpose, another option is to delegate these tasks to edge computing devices through fog computing, which offers benefits such as reduced energy consumption, enhanced security, and lower maintenance requirements [25,26]. Regardless of the approach, smart cities use sensors to monitor various parameters, including air and water quality, energy consumption, and traffic flow [27]. As cities transform into smart cities, leveraging data across sectors is crucial for collaboration, better decision-making, and improved urban services, such as transportation and environmental sustainability [28-30]. This highlights the necessity of utilizing modern technologies to manage this data effectively [31].

Communication is essential for the functioning of smart cities, with IoT technology facilitating the integration of various urban systems, including transportation networks. The efficiency of data collection through IoT is expected to peak with the advent of 5G and 6G technologies, making the development of IoT-powered smart networks crucial for smart city growth [32]. Additionally, cyber-physical systems enhance intelligence in areas like smart transportation, while edge technologies improve the connectivity of smart devices [33-35]. Smart cities also leverage digital information technologies to enhance urban management and services more intelligently [36]. These improvements span across smart infrastructure, public services, industrial systems, resource integration, security, and human development. As a result, cities can achieve scientific development, efficient management, and improved quality of life for their citizens. The network infrastructure and digital technologies employed in smart city construction have also spurred growth in service industries such as data services, software development, and business services [37-39].

Urban policymakers often view the integration of information and communication technologies (ICTs) into urban planning and management as an effective strategy for making cities smarter [40]. Notable examples of such technological advancements include the Vehicle2Grid system in Amsterdam, which stores locally produced energy in electric car batteries; London's Datastore, which gathers metadata, commentary, and visualizations from various sources; New York City's Lowline project, a solar-powered underground park; and the "5G Ecosystem" in Espoo, Finland, which offers ultra-fast Internet connectivity [2].

Various technologies play a crucial role in the creation and development of smart cities, directly impacting urban management, enhancing citizens' quality of life, and increasing productivity. One key technology in this context is the Internet of Things (IoT), which enables the connectivity and communication of devices and sensors, facilitating the collection of vital data from different city sectors, including transportation, energy, and the environment. This data can aid municipalities and urban planners in making better decisions. Advanced telecommunications technologies, such as 5G and 6G, provide the necessary bandwidth for rapid data transmission, enhancing real-time communication capabilities. Artificial Intelligence (AI) also contributes by analyzing data and making intelligent decisions to optimize public services, such as traffic management, energy management, and security. For example, smart traffic systems can use data collected from sensors to improve traffic flow and help reduce congestion. Additionally, blockchain technology plays a vital role in ensuring transparency and security in data management and digital transactions, particularly in financial systems and public services. Cyber-Physical Systems (CPS) and edge computing also enhance network and infrastructure efficiency through local data processing, which leads to reduced latency and improved user experiences.

Another important aspect of technology in smart cities is the use of Business Intelligence (BI). Business Intelligence refers to a broad array of analytical software and solutions designed to collect, consolidate, analyze, and present information. The primary goal of BI is to empower business users to make informed decisions by providing them with relevant insights [41]. By transforming complex internal and competitive data into accessible formats, BI tools facilitate strategic planning and decision-making for internal stakeholders. The implementation of BI solutions aims to enhance overall business performance by enabling organizations to identify trends, uncover opportunities, and optimize operations.These technologies assist urban organizations and authorities in extracting actionable and strategic insights from the collected data. By analyzing this data, decision-makers can identify existing trends and patterns, leading to improvements in public service performance, optimal resource allocation, and smarter urban planning. The implementation of innovative technologies and Business Intelligence in smart cities paves the way for sustainable development and the creation of intelligent and efficient urban environments.

In the context of smart cities, leveraging Business Intelligence (BI) strategies is crucial for effective urban management and decision-making. BI enables city administrators and stakeholders to gather, analyze, and interpret vast amounts of data from various sectors, such as transportation, energy, and public services. The integration of BI tools allows for informed decisions that improve efficiency and enhance the quality of life for citizens. Given the complexity and the wide range of BI strategies available, it is essential to prioritize and rank these strategies based on their influence and impact on smart city development. Utilizing methods such as the Fermatean Fuzzy-based TOPSIS allows for a more comprehensive and precise evaluation of these factors, ensuring that the most critical BI strategies are effectively implemented for sustainable and intelligent urban growth.

2. Literature Review

Over the past two decades, research on smart cities and digital deployment has increased globally, despite the distinct characteristics and uniqueness of each city [42-44]. These studies and practices have been approached from various perspectives [45], carried out by a wide range of scholars and actors, with a predominant focus from the technology sector, often emphasizing their specific interests [46].

Many studies have explored different facets of smart cities. For example, Naprathansuk [47] examined smart city policies in the provinces of Phuket, Khon Kaen, and Chiang Mai, utilizing the smart city concept to offer valuable data and recommendations for the executive committee. Similarly, Kamnuansilpa et al. [48] investigated citizens' awareness and understanding of Khon Kaen Smart City (KKSC) in Thailand. Yan et al. [49] present AI as a groundbreaking technology for improving smart city infrastructure, particularly in areas such as transportation, public safety, and healthcare. They highlight that the integration of AI into smart cities leads to an enhanced quality of life. For example, Kumar et al. [50] demonstrate that AI plays a critical role in the development of smart parking systems, where neural network-based algorithms facilitate automated parking. Additionally, Papastefanopoulos et al. [51] emphasize the use of AI in time series forecasting, which contributes to the overall performance enhancement of smart cities.

The development of IoT-based platforms for data sharing in smart cities places increased importance on security measures [33]. In line with this, Shari and Malip [52] emphasize that smart technology serves as a means to enhance security. They particularly point out that blockchain has the capability to provide a secure platform for storing and exchanging data across different sectors within smart cities, including transportation. Alaeddini et al. [53] highlight the importance of integrating AI with blockchain to achieve sustainability objectives in smart cities. According to the results in [34] , the combination of blockchain and AI is viewed positively as an effective approach for attaining sustainability and improving supply chain efficiency. Moreover, Yu et al. [54] demonstrate that merging IoT with blockchain enhances the security and privacy of IoT-based platforms.

In [55] a qualitative study was carried out to explore the steps required for Thailand to evolve into a smart city, as well as the challenges associated with the rapid development of such cities. The findings indicated that the process of becoming a smart city includes preparing the necessary infrastructure, implementing projects over a two-year period, and obtaining certification from the Digital Economy Promotion Agency (DEPA).

Han and kim [56] conducted a systematic analysis of 90 smart city articles from an urban context perspective, using the 'Urban Engagement and Impact Analytical Framework.' Many previous reviews of smart cities were carried out through bibliometric analysis from a holistic viewpoint, focusing on performance, trends, and research areas. The primary objective of their study was to explore the gap in the adequacy of smart city research's engagement with diverse urban contexts, aiming to create a smart urban environment centered on Smart Urbanism. The findings of the review aim to guide smart city research towards practical interventions in urban planning by engaging more deeply with urban contexts, ultimately contributing to the development of sustainable urban living for inhabitants by broadening the view of smart city development towards smart urbanism within urban environments.

In their study, Dashkevych and Portnov [2] proposed a relatively simple smart city ranking system based on two fundamental principles: direct relevance to human welfare and equal representation of key sustainability dimensions. The proposed assessment system, consisting of nine quantitative metrics, was applied to over 100 major cities worldwide, helping to identify the best and worst SC performers. As the study reveals, there are clear regional differences in the interpretation of components and underlying dimensions of SCs, with an emphasis on "economy and technology" in North America, "the environment" in Europe, and "society" in Asia. Rana et al. [1] in their study, aimed to identify the key barriers to smart city development by reviewing existing literature and gathering expert opinions in the field. Their work also attempted to prioritize these barriers, determining the most critical category and ranking specific barriers within each category for smart city development in India. Through a review of the literature, they identified 31 barriers and categorized them into six groups. The research applied the fuzzy Analytic Hierarchy Process (AHP) technique to prioritize the selected barriers. The findings revealed that "Governance" emerged as the most significant barrier category, followed by "Economic," "Technology," "Social," "Environmental," and "Legal and Ethical" categories.

Although extensive research has been conducted on various aspects of smart cities and the adoption of advanced technologies like AI [49-51], IoT [33, 54, 57, 58], and blockchain [52, 53, 59, 60], there remains a clear gap in the literature concerning the ranking and prioritization of Business Intelligence (BI) strategies specifically designed for smart cities. Numerous studies have examined smart city policies, infrastructure development, and technological innovations, such as AI-powered urban services and IoT-driven platforms. However, few have focused on systematically evaluating BI strategies, which are crucial for enhancing data-driven decision-making and effective urban management. Given the complexity and distinctiveness of smart cities, it is vital to prioritize these BI strategies to enable cities to utilize data more effectively for improving public services, urban planning, and sustainability. This study aims to address this gap by applying the Fermatean Fuzzy-based TOPSIS method to rank the most influential BI factors, offering valuable insights for decision-makers involved in smart city development. Table 2 presents a set of key influential criteria in smart cities, which have been extracted from the literature.

Table 2
Key criteria for smart city evaluation

	Criteria	Reference
C1	Smart Transportation	[21], [28], [41], [61], [62], [63]
C2	Integrated Urban Systems	[32], [61], [64], [65]
C3	Citizen Engagement	[26], [41], [56], [66], [67]
C4	Urban Innovation and Competitiveness	[2], [22], [41], [68]
C5	Environmental Sustainability	[41], [61], [69], [70], [71]
C6	Digitalization of Infrastructure	[37], [38], [43], [72], [73]
C7	Quality of Life for Citizens	[7], [17], [69], [74]
C8	Access to Urban Services	[31], [33], [61], [67]
C9	Urban Monitoring Systems	[4], [27], [62], [75]
C10	Data Aggregation from Various Sources	[62], [64], [74], [76], [77]
C11	Urban Condition Forecasting	[4], [7], [24], [51], [74]
C12	Resource Optimization	[17], [37], [38], [78]
C13	Investment Transparency	[36], [42], [72], [79]
C14	Renewable Resources	[27], [40], [41], [42]
C15	Operational Costs	[10], [11], [28], [80]

These criteria are used to assess and prioritize five main operational strategies for smart city development, which have been frequently mentioned in previous studies. The mentioned strategies are listed in Table 3.

Table 3
Key strategies for smart city development

	Strategy	Reference
S1	Big Data Analytics for Smart Decision-Making	[6], [19], [24], [31], [52], [64]
S2	Development of IoT-enabled Smart Networks	[32], [33], [34], [54]
S3	Cloud Platform Integration for Seamless Access to Data and Services	[25], [26], [49], [64]
S4	Artificial Intelligence Deployment for Predictive Analytics and Process Optimization	[34], [43], [49], [50], [51], [81]
S5	Process Automation and Deployment of Robotic Systems	Experts

3. Methodology

3.1 Fermatean Fuzzy TOPSIS

The MCDM (Multi-Criteria Decision-Making) problem is a challenge where evaluation results can not be effectively represented by a single attribute or criteria. One of the classical approaches for addressing this is the TOPSIS method, which ranks alternatives by determining their proximity to both a positive ideal solution and a negative ideal solution. The ideal alternative is the one closest to the positive ideal and farthest from the negative ideal. TOPSIS is beneficial because it accommodates different types of attributes, providing a clear and efficient way to rank alternatives through a set of comprehensive criteria. Over time, fuzzy methods have evolved from Intuitionistic Fuzzy Sets (IFS) to Pythagorean Fuzzy Sets (PFS), and more recently to Fermatean Fuzzy Sets (FFS), which broaden the scope of information that can be represented. This article aims to combine the strengths of TOPSIS with fermatean fuzzy sets to assess the quality of data assets, following specific procedural steps for this evaluation [82-85].

Step 1: Establish the decision matrix.

Based on the MCDM problem using Fermatean fuzzy sets, let's assume there are m evaluation objects $S_i(i = 1,2, \dots, m)$ and n evaluation criteria $C_j(j = 1,2, \dots, n)$. We have the weight vector for each evaluation criterion $= (w_1, w_2, \dots, w_n)$, $0 \le w_j \le 1$, $\sum_{j=1}^{n} w_j = 1$. We use $C_j(S_i) = (\mu_{ij}, v_{ij})$ to represent the evaluation value of alternative S_i for evaluation criterion C_j. The Fermatean fuzzy decision matrix is represented as follows $R = (C_j(S_i))_{m\times n}$. μ_{ij} , v_{ij} respectively represent membership degree and non-membership degree. The experts' opinions were transformed into Fermatean fuzzy numbers using Table 4.

Table 4
The relationship between linguistic variables and Fermatean fuzzy numbers was evaluated

Benefit type criteria	Very poor	Poor	Relatively poor	General
Cost type criteria	Very good	Good	Relatively good	General
Fermatean fuzzy numbers	(0, 1)	(0.17, 0.85)	(0.34, 0.68)	(0.51, 0.51)
Benefit type criteria	Relatively good	Good	Very good	
Cost type criteria	Relatively poor	Poor	Very poor	
Fermatean fuzzy numbers	(0.68, 0.34)	(0.85, 0.17)	(1, 0)	

Step 2: Determine the positive ideal solution and negative ideal solution

To determine Fermatean Fuzzy Positive Ideal Solution (FFPIS) and Fermatean Fuzzy Negative Ideal Solution (FFNIS), Equations 1 and 2 were used. Equation 1 is applied to calculate the FFPIS. If the criterion is a benefit, the highest score among the experts' opinions is selected as the FFPIS. If the criterion is a cost, the lowest score is chosen as the FFPIS. Equation 2 is used to calculate the FFNIS. If the criterion is a benefit, the lowest score among the experts' opinions is selected as the FFNIS. If the criterion is a cost, the highest score is chosen as the FFNIS.

$$S^{+} = \begin{cases} max\left\langle score(C_j(S_i))\right\rangle \mid j = 1,2,\dots,n \quad (If\ C_j\ is\ a\ benefit\ criteria) \\ min\left\langle score(C_j(S_i))\right\rangle \mid j = 1,2,\dots,n \quad (If\ C_j\ is\ a\ cost\ criteria) \end{cases} \tag{1}$$
$$= \{(\mu_1^{+}, \upsilon_1^{+}), (\mu_2^{+}, \upsilon_2^{+}), \dots, (\mu_n^{+}, \upsilon_n^{+})\}$$

$$S^{-} = \begin{cases} min\left\langle score(C_j(S_i))\right\rangle \mid j = 1,2,\dots,n \quad (If\ C_j\ is\ a\ benefit\ criteria) \\ max\left\langle score(C_j(S_i))\right\rangle \mid j = 1,2,\dots,n \quad (If\ C_j\ is\ a\ cost\ criteria) \end{cases} \tag{2}$$
$$= \{(\mu_1^{-}, \upsilon_1^{-}), (\mu_2^{-}, \upsilon_2^{-}), \dots, (\mu_n^{-}, \upsilon_n^{-})\}$$

Step 3: Calculate the distance between each alternative and the fermatean fuzzy positive and negative ideal solutions.

Equations 3 and 4 were used to calculate the distance from the fermatean fuzzy positive and negative ideal solutions, respectively.

$$\begin{aligned} D\left(S_i, S^{+}\right) &= \sum_{j=1}^{n} w_j d\left(C_j(S_i), C_j(S^{+})\right) \\ &= \frac{1}{2} \times \sum_{j=1}^{n} w_j \sqrt{\frac{1}{2} \times \left[\left(\mu_{ij}^3 - (\mu_j^{+})^3\right)^2 + \left(\upsilon_{ij}^3 - (\upsilon_j^{+})^3\right)^2 + \left(\pi_{ij}^3 - (\pi_j^{+})^3\right)^2\right]} \qquad i = 1,2,\dots,m \end{aligned} \tag{3}$$

$$\begin{aligned} D\left(S_i, S^{-}\right) &= \sum_{j=1}^{n} w_j d\left(C_j(S_i), C_j(S^{-})\right) \\ &= \frac{1}{2} \times \sum_{j=1}^{n} w_j \sqrt{\frac{1}{2} \times \left[\left(\mu_{ij}^3 - (\mu_j^{-})^3\right)^2 + \left(\upsilon_{ij}^3 - (\upsilon_j^{-})^3\right)^2 + \left(\pi_{ij}^3 - (\pi_j^{-})^3\right)^2\right]} \qquad i = 1,2,\dots,m \end{aligned} \tag{4}$$

Where π_{ij} indicates the hesitancy degree and is calculated using Equation 5.

$$\pi_{ij} = \sqrt[3]{1-\mu_{ij}^3-\upsilon_{ij}^3} \tag{5}$$

Step 4: Calculate the Relative Closeness (RC) index for each alternative using Equation 6.

$$RC(S_i) = \frac{D(S_i, S^-)}{\left[D(S_i, S^+) + D(S_i, S^-)\right]} \tag{6}$$

Step 5: Determine the optimal ranking of alternatives and analyze the results.

4. Results

In this section, the research findings are presented in detail. In step 1, the experts' opinions were collected based on Table 4 and were aggregated using the mean. The integrated opinions are displayed in Table 5, represented by the symbols μ and υ. According to Equation 5, the hesitancy degree was calculated using the values of μ and υ, and the results are shown in Table 5, denoted by the symbol π. This table shows initial fermatean fuzzy decision matrix.

Table 5
Fermatean Fuzzy Integrated Decision Matrix

	C1			C2			C3			C4			C5		
	μ	υ	π	μ	υ	π	μ	υ	π	μ	υ	π	μ	υ	π
S1	0.925	0.085	0.069	0.765	0.255	0.179	0.595	0.425	0.238	0.425	0.595	0.238	0.255	0.765	0.179
S2	0.765	0.255	0.179	0.925	0.085	0.069	0.765	0.255	0.179	0.765	0.255	0.179	0.595	0.425	0.238
S3	0.425	0.595	0.238	0.925	0.085	0.069	0.925	0.085	0.069	0.595	0.425	0.238	0.425	0.595	0.238
S4	0.425	0.595	0.238	0.595	0.425	0.238	0.255	0.765	0.179	0.765	0.255	0.179	0.595	0.425	0.238
S5	0.765	0.255	0.179	0.765	0.255	0.179	0.925	0.085	0.069	0.595	0.425	0.238	0.425	0.595	0.238
	C6			C7			C8			C9			C10		
S1	0.595	0.425	0.238	0.595	0.425	0.238	0.425	0.595	0.238	0.255	0.765	0.179	0.595	0.425	0.238
S2	1	0	0	1	0	0	0.765	0.255	0.179	1	0	0	0.765	0.255	0.179
S3	0.765	0.255	0.179	0.595	0.425	0.238	1	0	0	0.765	0.255	0.179	0.925	0.085	0.069
S4	0.595	0.425	0.238	0.765	0.255	0.179	0.595	0.425	0.238	0.595	0.425	0.238	0.255	0.765	0.179
S5	1	0	0	0.595	0.425	0.238	0.765	0.255	0.179	0.925	0.085	0.069	0.925	0.085	0.069
	C11			C12			C13			C14			C15		
S1	0.765	0.255	0.179	0.595	0.425	0.238	0.425	0.595	0.238	0.255	0.765	0.179	0.425	0.595	0.238
S2	0.595	0.425	0.238	0.255	0.765	0.179	0.255	0.765	0.179	0.425	0.595	0.238	0.255	0.765	0.179
S3	0.425	0.595	0.238	0.425	0.595	0.238	0.595	0.425	0.238	0.425	0.595	0.238	0.255	0.765	0.179
S4	1	0	0	0.765	0.255	0.179	0.255	0.765	0.179	0.595	0.425	0.238	0.765	0.255	0.179
S5	0.425	0.595	0.238	0.595	0.425	0.238	0.765	0.255	0.179	0.425	0.595	0.238	0.425	0.595	0.238

Table 6 shows the Fermatean Fuzzy Positive Ideal Solution (FFPIS) and Fermatean Fuzzy Negative Ideal Solution (FFNIS) which are calculated according to Equations 1 and 2 in step 2. Since all the criteria were benefit type, the highest score in each column was selected as FFPIS, while the lowest score in each column was chosen as FFNIS.

Table 6
Fermatean Fuzzy Positive and Negative Ideal Solution

	C1			C2			C3			C4			C5		
	μ	υ	π	μ	υ	π	μ	υ	π	μ	υ	π	μ	υ	π
S+	0.925	0.085	0.069	0.925	0.085	0.069	0.925	0.085	0.069	0.765	0.255	0.179	0.595	0.425	0.179
S-	0.425	0.595	0.238	0.595	0.425	0.238	0.255	0.765	0.238	0.425	0.595	0.238	0.255	0.765	0.238
	C6			C7			C8			C9			C10		
S+	1.000	0.000	0.000	1.000	0.000	0.000	1.000	0.000	0.000	1.000	0.000	0.000	0.925	0.085	0.069
S-	0.595	0.425	0.238	0.595	0.425	0.238	0.425	0.595	0.238	0.255	0.765	0.238	0.255	0.765	0.238

	C11			C12			C13			C14			C15		
S+	1.000	0.000	0.000	0.765	0.255	0.179	0.765	0.255	0.179	0.595	0.425	0.179	0.765	0.255	0.179
S-	0.425	0.595	0.238	0.255	0.765	0.238	0.255	0.765	0.238	0.255	0.765	0.238	0.255	0.765	0.238

In step 3, for each alternative, the distance from the fermatean fuzzy positive ideal solution was calculated using Equation 3 (Table 8). The sum of these distances for each alternative was then calculated, resulting in the final value of D (Si, S^+). Table 9 also shows the distance from the fermatean fuzzy negative ideal solution (D (Si, S-)) which is obtained using Equation 4. It is worth mentioning that the weight vector of the criteria, as determined by the experts, is presented in Table 7.

Table 7
Weight vector of the criteria

	C1	C2	C3	C4	C5
W_j	0.0768	0.0760	0.0633	0.0681	0.0609
	C6	C7	C8	C9	C10
W_j	0.0771	0.0657	0.0736	0.0681	0.0736
	C11	C12	C13	C14	C15
W_j	0.0673	0.0554	0.0507	0.0649	0.0586

Table 8
The distance from the positive ideal solution

	C1	C2	C3	C4	C5	C6	C7	C8
S1	0.0000	0.0185	0.0262	0.0202	0.0180	0.0432	0.0368	0.0493
S2	0.0187	0.0000	0.0154	0.0000	0.0003	0.0000	0.0000	0.0288
S3	0.0404	0.0000	0.0000	0.0118	0.0082	0.0301	0.0368	0.0000
S4	0.0404	0.0315	0.0401	0.0000	0.0003	0.0432	0.0257	0.0413
S5	0.0187	0.0185	0.0000	0.0118	0.0082	0.0000	0.0368	0.0288
	C9	C10	C11	C12	C13	C14	C15	D (Si , S+)
S1	0.0520	0.0305	0.0263	0.0096	0.0150	0.0192	0.0173	0.1911
S2	0.0000	0.0179	0.0377	0.0239	0.0218	0.0087	0.0253	0.0993
S3	0.0266	0.0000	0.0451	0.0164	0.0088	0.0087	0.0253	0.1291
S4	0.0382	0.0466	0.0000	0.0000	0.0218	0.0004	0.0000	0.1647
S5	0.0100	0.0000	0.0451	0.0096	0.0000	0.0087	0.0173	0.1067

Table 9
The distance from the negative ideal solution

	C1	C2	C3	C4	C5	C6	C7	C8
S1	0.0404	0.0131	0.0187	0.0000	0.0003	0.0000	0.0000	0.0000
S2	0.0227	0.0315	0.0273	0.0202	0.0180	0.0432	0.0368	0.0218
S3	0.0000	0.0315	0.0401	0.0091	0.0105	0.0133	0.0000	0.0493
S4	0.0000	0.0000	0.0003	0.0202	0.0180	0.0000	0.0114	0.0099
S5	0.0227	0.0131	0.0401	0.0091	0.0105	0.0432	0.0000	0.0218
	C9	C10	C11	C12	C13	C14	C15	D (Si , S-)
S1	0.0004	0.0218	0.0199	0.0164	0.0088	0.0004	0.0101	0.0752
S2	0.0520	0.0317	0.0090	0.0003	0.0003	0.0112	0.0003	0.1632
S3	0.0293	0.0466	0.0000	0.0096	0.0150	0.0112	0.0003	0.1329
S4	0.0201	0.0004	0.0451	0.0239	0.0003	0.0192	0.0253	0.0970
S5	0.0431	0.0466	0.0000	0.0164	0.0218	0.0112	0.0101	0.1549

To finalize the ranking of strategies, the Relative Closeness (RC) index was calculated using Equation 6 and is shown in Table 10. This is designed based on the distances from the negative and positive ideal solutions. According to the RC index, the ranking of the strategies has been determined. The strategies S2, S5, S3, S4, and S1 were ranked first to fifth, respectively.

Table 10
The final ranking of alternatives

	D (Si , S+)	D (Si , S-)	RC	RANK
S1	0.1911	0.0752	0.2824	5
S2	0.0993	0.1632	0.6219	1
S3	0.1291	0.1329	0.5074	3
S4	0.1647	0.0970	0.3706	4
S5	0.1067	0.1549	0.5921	2

4. Conclusion

This research aimed to rank business intelligence-based strategies for smart cities, focusing on five strategies designed for smart city development. These strategies are Big Data Analytics for Smart Decision-Making (S1), development of IoT-enabled smart networks (S2), Cloud Platform Integration for Seamless Access to Data and Services (S3), Artificial Intelligence Deployment for Predictive Analytics and Process Optimization (S4), and Process Automation and Deployment of Robotic Systems (S5). The Fermatean Fuzzy-Based TOPSIS method was employed for ranking, using 15 criteria derived from prior studies on smart cities. Expert opinions were used to weigh these criteria. As shown in Table 6, the first to fifth highest weights are assigned to the following criteria in order: Smart Transportation (C1), Integrated Urban Systems (C2), Digitalization of Infrastructure (C6) and Access to Urban Services (C8), and Data Aggregation from Various Sources (C10).

The results of the Fermatean Fuzzy-Based TOPSIS indicate that development of IoT-enabled smart networks (S2) is the top-ranked strategy for supporting smart cities. This approach enhances urban service performance and quality by connecting and integrating various devices, sensors, and infrastructure across the city. IoT-equipped smart networks enable real-time monitoring of energy consumption, optimizing resource management. By collecting and analyzing data on electricity, water, and gas consumption, these systems facilitate consumption forecasting and resource distribution optimization. For example, smart street lighting can automatically adjust based on traffic and environmental conditions, leading to reduced energy consumption.

IoT enables smart transportation networks to continuously gather and analyze data on traffic conditions, vehicle movements, and air pollution. This information allows for improved traffic management and directs users to optimal routes. Additionally, car-sharing systems and optimized public transportation management can reduce private vehicle use and decrease air pollution. IoT networks also collect environmental data to predict natural disasters like floods and earthquakes, sending immediate alerts and coordinating emergency services to minimize damage. During crises, IoT enhances crisis management by facilitating communication between urban systems, such as hospitals and emergency centers.

The strategy of process automation and deployment of robotic systems (S5) ranks second as a fundamental element in developing smart cities. This approach optimizes processes and boosts efficiency across urban sectors, leading to cost savings and improved service quality, thereby significantly advancing smart city initiatives. A key advantage of process automation is the reduction of time and human error. For example, using automated robots in transportation and logistics can enhance traffic flow and minimize accidents caused by human mistakes. Robotic systems can autonomously manage public transportation, enabling vehicles to adhere to more precise schedules and increasing overall efficiency. Additionally, process automation and robotic systems can enhance waste management and recycling efforts. Smart robots can sort and recycle reusable materials more effectively, improving recycling efficiency and reducing environmental impacts. Overall, implementing automation and robotic systems in smart cities can enhance citizens' quality of life, boost economic productivity, and lessen environmental effects.

The strategy of cloud platform integration for seamless access to data and service (S3) is crucial for enhancing smart cities. This approach allows the collection and management of data from sensors, cameras, and other digital sources in a centralized environment, facilitating real-time information access and analysis. By connecting data from various sources, it is readily available to city managers, businesses, and citizens, reducing processing time and costs while improving data-driven decision-making. For example, municipalities can manage traffic more effectively and plan public transportation with up-to-date traffic information. Furthermore, urban services like waste management, public health, and security can operate more efficiently with continuous data access.

The strategy of artificial Intelligence deployment for predictive analytics and process optimization (S4) ranks fourth and is vital for the growth of smart cities. AI implementation enhances the efficiency of systems and processes, aiding decision-makers in reducing resource waste, increasing productivity, and improving citizens' quality of life. Through machine learning algorithms, AI can predict traffic patterns and optimize public transportation. For example, anticipating peak-hour traffic and adjusting traffic lights accordingly can alleviate congestion and reduce air pollution. AI also helps create smart routes for public transport fleets.

Moreover, AI optimizes energy and water consumption by using predictive algorithms to forecast future consumption and adjust distribution systems, promoting sustainable resource management. By analyzing waste generation data, AI identifies the best times and locations for waste collection, creating efficient routes for collection fleets. This approach saves time and costs while minimizing carbon emissions and enhancing urban service efficiency.

The strategy of utilizing big data analytics for smart decision-making (S1) ranks fifth and is pivotal to the growth of smart cities. Big data analytics enhances the development of smart cities by leveraging extensive datasets, leading to more precise and optimized urban management decisions. This analysis reveals insights into traffic patterns, public transportation systems, and commuting behaviors, enabling the identification of congestion and the recommendation of optimized routes. Additionally, predicting peak-hour traffic and suggesting alternatives improves citizens' experiences.

Furthermore, by gathering and analyzing citizen feedback from social media and surveys, city managers gain a clearer understanding of community needs and preferences. This data-driven approach informs policies and decisions, aligning them with citizen priorities. Analyzing demographic and economic data also helps city officials plan infrastructure development accurately, forecasting future requirements for schools, hospitals, and public spaces to enhance resource efficiency and productivity.

Conflicts of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgement

This research was not funded by any grant.

References

[1] Rana, N. P., Luthra, S., Mangla, S. K., Islam, R., Roderick, S., & Dwivedi, Y. K. (2019). Barriers to the Development of Smart Cities in Indian Context. Information Systems Frontiers, 21(3), 503–525. https://doi.org/10.1007/s10796-018-9873-4

[2] Dashkevych, O., & Portnov, B. A. (2022). Criteria for smart city identification: A systematic literature review. Sustainability, 14(8), 4448. https://doi.org/10.3390/su14084448
[3] Choi, H.-S., & Song, S.-K. (2022). Direction for a transition toward smart sustainable cities based on the diagnosis of smart city plans. Smart Cities, 6(1), 156–178. https://doi.org/10.3390/smartcities6010009
[4] Marsal-Llacuna, M.-L., Colomer-Llinàs, J., & Meléndez-Frigola, J. (2015). Lessons in urban monitoring taken from sustainable and livable cities to better address the Smart Cities initiative. Technological Forecasting and Social Change, 90, 611–622. https://doi.org/10.1016/j.techfore.2014.01.012
[5] Regalia, B., McKenzie, G., Gao, S., & Janowicz, K. (2016). Crowdsensing smart ambient environments and services. Transactions in GIS, 20(3), 382–398. https://doi.org/10.1111/tgis.12233
[6] Estrada, E., Martinez Vargas, M. P., Gómez, J., Peña Pérez Negron, A., López, G. L., & Maciel, R. (2019). Smart cities big data algorithms for sensors location. Applied Sciences, 9(19), 4196. https://doi.org/10.3390/app9194196
[7] Trencher, G. (2019). Towards the smart city 2.0: Empirical evidence of using smartness as a tool for tackling social challenges. Technological Forecasting and Social Change, 142, 117–128. https://doi.org/10.1016/j.techfore.2018.07.033
[8] Toli, A. M., & Murtagh, N. (2020). The concept of sustainability in smart city definitions. Frontiers in Built Environment, 6, 77. https://doi.org/10.3389/fbuil.2020.00077
[9] Marine-Roig, E., & Clavé, S. A. (2015). Tourism analytics with massive user-generated content: A case study of Barcelona. Journal of Destination Marketing & Management, 4(3), 162–172. https://doi.org/10.1016/j.jdmm.2015.06.004
[10] Perng, S.-Y., Kitchin, R., & Mac Donncha, D. (2018). Hackathons, entrepreneurial life and the making of smart cities. Geoforum, 97, 189–197. https://doi.org/10.1016/j.geoforum.2018.08.024
[11] Yigitcanlar, T., & Cugurullo, F. (2020). The sustainability of artificial intelligence: An urbanistic viewpoint from the lens of smart and sustainable cities. Sustainability, 12(20), 8548. https://doi.org/10.3390/su12208548
[12] Vinod Kumar, T. M. (Ed.). (2017). Smart Economy in Smart Cities: International Collaborative Research: Ottawa, St.Louis, Stuttgart, Bologna, Cape Town, Nairobi, Dakar, Lagos, New Delhi, Varanasi, Vijayawada, Kozhikode, Hong Kong. Springer Singapore. https://doi.org/10.1007/978-981-10-1610-3
[13] Correia, D., Marques, J. L., & Teixeira, L. (2022). The state-of-the-art of smart cities in the European union. Smart Cities, 5(4), 1776–1810. https://doi.org/10.3390/smartcities5040089
[14] Kim, H. M., Sabri, S., & Kent, A. (2021). Smart cities as a platform for technological and social innovation in productivity, sustainability, and livability: A conceptual framework. In Smart cities for technological and social innovation (pp. 9–28). Elsevier. https://doi.org/10.1016/B978-0-12-818886-6.00002-2
[15] Bouramdane, A.-A. (2023). Optimal water management strategies: Paving the way for sustainability in smart cities. Smart Cities, 6(5), 2849–2882. https://doi.org/10.3390/smartcities6050128
[16] Gracias, J. S., Parnell, G. S., Specking, E., Pohl, E. A., & Buchanan, R. (2023). Smart cities—A structured literature review. Smart Cities, 6(4), 1719–1743. https://doi.org/10.3390/smartcities6040080
[17] Pandiyan, P., Saravanan, S., Usha, K., Kannadasan, R., Alsharif, M. H., & Kim, M.-K. (2023). Technological advancements toward smart energy management in smart cities. Energy Reports, 10, 648–677. https://doi.org/10.1016/j.egyr.2023.07.021
[18] Nam, T., & Pardo, T. A. (2011). Smart city as urban innovation: Focusing on management, policy, and context. Proceedings of the 5th International Conference on Theory and Practice of Electronic Governance, 185–194. https://doi.org/10.1145/2072069.2072100
[19] Parasol, M. (2018). The impact of China's 2016 Cyber Security Law on foreign technology firms, and on China's big data and Smart City dreams. Computer Law & Security Review, 34(1), 67–98. https://doi.org/10.1016/j.clsr.2017.05.022
[20] Mishra, R. K., Kumari, C. L., Janaki Krishna, P. S., & Dubey, A. (2022). Smart Cities for Sustainable Development: An Overview. In R. K. Mishra, C. L. Kumari, S. Chachra, P. S. J. Krishna, A. Dubey, & R. B. Singh (Eds.), Smart Cities for Sustainable Development (pp. 1–12). Springer Nature Singapore. https://doi.org/10.1007/978-981-16-7410-5_1
[21] Solanki, A. S., Patel, C., & Doshi, N. (2019). Smart cities-A case study of Porto and Ahmedabad. Procedia Computer Science, 160, 718–722. https://doi.org/10.1016/j.procs.2019.11.021
[22] Nagy, Z., Szep, T. S., & Szendi, D. (2019). Regional Disparities in Hungarian Urban Energy Consumption-A Link between Smart Cities and Successful Cities. Geographia Technica, 14(1), 92–102. http://dx.doi.org/10.21163/GT_2019.
[23] Patel, Y., & Doshi, N. (2019). Social implications of smart cities. Procedia Computer Science, 155, 692–697. https://doi.org/10.1016/j.procs.2019.08.099
[24] Morello, R., Mukhopadhyay, S. C., Liu, Z., Slomovitz, D., & Samantaray, S. R. (2017). Advances on sensing technologies for smart cities and power grids: A review. IEEE Sensors Journal, 17(23), 7596–7610. https://doi.org/10.1109/JSEN.2017.2735539

[25] Kanaya, T., Nakao, A., Yamamoto, S., Oguchi, M., & Yamaguchi, S. (2020). Edge computing for IoT sensors based on DPN. 2020 IEEE International Conference on Consumer Electronics-Taiwan (ICCE-Taiwan), 1–2. https://doi.org/10.1109/ICCE-Taiwan49838.2020.9258322

[26] Qi, Q., & Tao, F. (2019). A smart manufacturing service system based on edge computing, fog computing, and cloud computing. IEEE Access, 7, 86769–86777. https://doi.org/10.1109/ACCESS.2019.2923610

[27] Astrain, J. J., Falcone, F., Lopez-Martin, A. J., Sanchis, P., Villadangos, J., & Matias, I. R. (2021). Monitoring of electric buses within an urban smart city environment. IEEE Sensors Journal, 22(12), 11364–11372. https://doi.org/10.1109/SENSORS47125.2020.9278791

[28] Arroub, A., Zahi, B., Sabir, E., & Sadik, M. (2016). A literature review on Smart Cities: Paradigms, opportunities and open problems. 2016 International Conference on Wireless Networks and Mobile Communications (WINCOM), 180–186. https://doi.org/10.1109/WINCOM.2016.7777211

[29] Khawaja, S., & Javidroozi, V. (2023). Blockchain technology as an enabler for cross-sectoral systems integration for developing smart sustainable cities. IET Smart Cities, 5(3), 151–172. https://doi.org/10.1049/smc2.12059

[30] Gharedaghi Kloucheh, S., Khoubanfar, H., Moghaddam Matin, M., & Behnam Rassouli, F. (2021). Investigating effects of galbanic acid on the viability of LoVo colon carcinoma cells. 21st International and 9th National Congress in Biology.

[31] Joyce, A., & Javidroozi, V. (2024). Smart city development: Data sharing vs. data protection legislations. Cities, 148, 104859. https://doi.org/10.1016/j.cities.2024.104859

[32] Al Amin, A., Hong, J., Bui, V.-H., & Su, W. (2023). Emerging 6G/B6G wireless communication for the power infrastructure in smart cities: Innovations, challenges, and future perspectives. Algorithms, 16(10), 474. https://doi.org/10.3390/a16100474

[33] Khalil, U., Malik, O. A., Uddin, M., & Chen, C.-L. (2022). A comparative analysis on blockchain versus centralized authentication architectures for IoT-enabled smart devices in smart cities: A comprehensive review, recent advances, and future research directions. Sensors, 22(14), 5168. https://doi.org/10.3390/s22145168

[34] Najafi, B., Najafi, A., Madanchi, F., Maghroor, H., & Taherdoost, H. (2024). The Impact of Cutting-Edge Technologies on Smart City Supply Chain: A Systematic Literature Review of the Evidence and Implications. IEEE Engineering Management Review. http://dx.doi.org/10.1109/EMR.2024.3373502

[35] Hosseini, F., Ahmadi, A., Hassanzade, H., Gharedaghi, S., Rassouli, F. B., & Jamialahmadi, K. (2024). Inhibition of melanoma cell migration and invasion by natural coumarin auraptene through regulating EMT markers and reducing MMP-2 and MMP-9 activity. European Journal of Pharmacology, 971, 176517. https://doi.org/10.1016/j.ejphar.2024.176517

[36] Camero, A., & Alba, E. (2019). Smart City and information technology: A review. Cities, 93, 84–94. https://doi.org/10.1016/j.cities.2019.04.014

[37] Pencarelli, T. (2020). The digital revolution in the travel and tourism industry. Information Technology & Tourism, 22(3), 455–476. https://doi.org/10.1007/s40558-019-00160-3

[38] Ji, X., Chen, J., & Zhang, H. (2024). Smart city construction empowers tourism: Mechanism analysis and spatial spillover effects. Humanities and Social Sciences Communications, 11(1), 1–14. https://doi.org/10.1057/s41599-024-03626-w

[39] Azad, M., Hosseini, F., Hassanzade, H., Gharedaghi, S., Mahdipour, E., Rassouli, F. B., & Jamialahmadi, K. (2024). Galbanic acid suppresses melanoma cell migration and invasion by reducing MMP activity and downregulating N-cadherin and fibronectin. Naunyn-Schmiedeberg's Archives of Pharmacology, 1–10. https://doi.org/10.1007/s00210-024-02981-4

[40] Sánchez-Corcuera, R., Nuñez-Marcos, A., Sesma-Solance, J., Bilbao-Jayo, A., Mulero, R., Zulaika, U., Azkune, G., & Almeida, A. (2019). Smart cities survey: Technologies, application domains and challenges for the cities of the future. International Journal of Distributed Sensor Networks, 15(6), 155014771985398. https://doi.org/10.1177/1550147719853984

[41] Babić, A., & Zron, A. (2024). Business Intelligence Tools in the Interpretation of the Ranking of Smart Cities. 2024 47th MIPRO ICT and Electronics Convention (MIPRO), 211–217. https://doi.org/10.1109/MIPRO60963.2024.10569892

[42] Burns, R., Fast, V., Levenda, A., & Miller, B. (2021). Smart cities: Between worlding and provincialising. Urban Studies, 58(3), 461–470. https://doi.org/10.1177/0042098020975982

[43] Dowling, R., McGuirk, P., Maalsen, S., & Sadowski, J. (2021). How smart cities are made: A priori, ad hoc and post hoc drivers of smart city implementation in Sydney, Australia. Urban Studies, 58(16), 3299–3315. https://doi.org/10.1177/0042098020986292

[44] Ahmadirad, Z. (2024). Evaluating the influence of AI on market values in finance: Distinguishing between authentic growth and speculative hype. International Journal of Advanced Research in Humanities and Law, 1(2), 50–57. https://doi.org/10.63053/ijrel.11

[45] Zhao, F., Fashola, O. I., Olarewaju, T. I., & Onwumere, I. (2021). Smart city research: A holistic and state-of-the-art literature review. Cities, 119, 103406. https://doi.org/10.1016/j.cities.2021.103406
[46] Han, M. J. N., & Kim, M. J. (2024). A systematic review of smart city research from an urban context perspective. Cities, 150, 105027. https://doi.org/10.1016/j.cities.2024.105027
[47] Naprathansuk, N. (2017). A national pilot project on smart city policy in Thailand: A case study on Phuket Khon Kaen Chiangmai Province. European Journal of Multidisciplinary Studies, 2(6), 337–346. http://dx.doi.org/10.26417/ejms.v6i1.p337-346
[48] Kamnuansilpa, P., Laochankham, S., Crumpton, C. D., & Draper, J. (2020). Citizen awareness of the smart city: A study of Khon Kaen, Thailand. The Journal of Asian Finance, Economics and Business, 7(7), 497–508. http://dx.doi.org/10.13106/jafeb.2020.vol7.no7.497
[49] Yan, Z., Jiang, L., Huang, X., Zhang, L., & Zhou, X. (2023). Intelligent urbanism with artificial intelligence in shaping tomorrow's smart cities: Current developments, trends, and future directions. Journal of Cloud Computing, 12(1), 179. https://doi.org/10.1186/s13677-023-00569-6
[50] Kumar, K., Singh, V., Raja, L., & Bhagirath, S. N. (2023). A review of parking slot types and their detection techniques for smart cities. Smart Cities, 6(5), 2639–2660. https://doi.org/10.3390/smartcities6050119
[51] Papastefanopoulos, V., Linardatos, P., Panagiotakopoulos, T., & Kotsiantis, S. (2023). Multivariate Time-Series Forecasting: A Review of Deep Learning Methods in Internet of Things Applications to Smart Cities. Smart Cities, 6(5), 2519–2552. https://doi.org/10.3390/smartcities6050114
[52] Shari, N. F. M., & Malip, A. (2022). State-of-the-art solutions of blockchain technology for data dissemination in smart cities: A comprehensive review. Computer Communications, 189, 120–147. https://doi.org/10.1016/j.comcom.2022.03.013
[53] Alaeddini, M., Hajizadeh, M., & Reaidy, P. (2023). A Bibliometric Analysis of Research on the Convergence of Artificial Intelligence and Blockchain in Smart Cities. Smart Cities, 6(2), 764–795. https://doi.org/10.3390/smartcities6020037
[54] Yu, Z., Song, L., Jiang, L., & Khold Sharafi, O. (2022). Systematic literature review on the security challenges of blockchain in IoT-based smart cities. Kybernetes, 51(1), 323–347. https://doi.org/10.1108/K-07-2020-0449
[55] Moolngearn, P., & Kraiwanit, T. (2024). BARRIERS TO DEVELOPMENT OF SMART CITIES: LESSONS LEARNED FROM AN EMERGING ECONOMY. https://doi.org/10.22495/cbsrv5i2art22
[56] Han, M. J. N., & Kim, M. J. (2021). A critical review of the smart city in relation to citizen adoption towards sustainable smart living. Habitat International, 108, 102312. https://doi.org/10.1016/j.habitatint.2021.102312
[57] Haseli, G., Sheikh, R., Wang, J., Tomaskova, H., & Tirkolaee, E. B. (2021). A novel approach for group decision making based on the best–worst method (G-bwm): Application to supply chain management. Mathematics, 9(16), 1881. https://doi.org/10.3390/math9161881
[58] Sepahi, T., Shahbazi, M., & Shafiei Roudposhti, M. (2020). Drug distribution system in Iran: A multi method study of defects and solutions. Depiction of Health, 11(4), 324–343. https://doi.org/10.34172/doh.2020.41
[59] Sheykhfard, A., Haghighi, F., Saeidi, S., SafariTaherkhani, M., & Das, S. (2024). Understanding the influence of environmental factors on driver speed: A structural equation modeling analysis. IATSS Research, 48(3), 427–439. https://doi.org/10.1016/j.iatssr.2024.08.001
[60] Hashemi, R., Farahi, M., Bagheri, R., Iranshahi, M., Torabinejad, S., Gharedaghi, S., & Soleymanifard, S. (2021). In vitro study of Radiosensitivity Effects of Galbanic Acid on ovarian tumor cells (OVCAR-3 cell line). Natural Product Communications, 16(10), 1934578X211046068. https://doi.org/10.1177/1934578X211046068
[61] Durán-Sánchez, A., De La Cruz Del Río-Rama, M., Sereno-Ramírez, A., & Bredis, K. (2017). Sustainability and Quality of Life in Smart Cities: Analysis of Scientific Production. In M. Peris-Ortiz, D. R. Bennett, & D. Pérez-Bustamante Yábar (Eds.), Sustainable Smart Cities (pp. 159–181). Springer International Publishing. https://doi.org/10.1007/978-3-319-40895-8_12
[62] Arneodo, F., Castelli, R., & Botta, D. (2017). Towards a "Smart Region" paradigm: Beyond Smart Cities borders: Piedmont Region experience. 2017 International Conference of Electrical and Electronic Technologies for Automotive, 1–8. https://doi.org/10.23919/EETA.2017.7993225
[63] Halimi, Z., SafariTaherkhani, M., & Cui, Q. (2024). A Generalized Framework for Assessing Equity in Ground Transportation Infrastructure: An Exploratory Study (arXiv:2409.19018). arXiv. https://doi.org/10.48550/arXiv.2409.19018
[64] Teich, T., Trommer, M., Börner, P., Härtel, T., Junghans, S., Leonhardt, S., Scharf, O., & Werner, P. (2017). Approach to develop innovative services through service networks by using ubiquitous infrastructures. 2017 IEEE SmartWorld, Ubiquitous Intelligence & Computing, Advanced & Trusted Computed, Scalable Computing & Communications, Cloud & Big Data Computing, Internet of People and Smart City Innovation (SmartWorld/SCALCOM/UIC/ATC/CBDCom/IOP/SCI), 1–7. https://doi.org/10.1109/UIC-ATC.2017.8397500

[65] Haseli, G., Torkayesh, A. E., Hajiaghaei-Keshteli, M., & Venghaus, S. (2023). Sustainable resilient recycling partner selection for urban waste management: Consolidating perspectives of decision-makers and experts. Applied Soft Computing, 137, 110120. https://doi.org/10.1016/j.asoc.2023.110120

[66] Nezhad, M. Z., Nazarian-Jashnabadi, J., Rezazadeh, J., Mehraeen, M., & Bagheri, R. (2023). Assessing dimensions influencing IoT implementation readiness in industries: A fuzzy DEMATEL and fuzzy AHP analysis. Journal of Soft Computing and Decision Analytics, 1(1), 102–123. https://doi.org/10.31181/jscda11202312

[67] Nazarian-Jashnabadi, J., Bonab, S. R., Haseli, G., Tomaskova, H., & Hajiaghaei-Keshteli, M. (2023). A dynamic expert system to increase patient satisfaction with an integrated approach of system dynamics, ISM, and ANP methods. Expert Systems with Applications, 234, 121010. https://doi.org/10.1016/j.eswa.2023.121010

[68] Mansourihanis, O., Maghsoodi Tilaki, M. J., Sheikhfarshi, S., Mohseni, F., & Seyedebrahimi, E. (2024). Addressing Urban Management Challenges for Sustainable Development: Analyzing the Impact of Neighborhood Deprivation on Crime Distribution in Chicago. Societies, 14(8), 139. https://doi.org/10.3390/soc14080139

[69] Grecu, V., Ciobotea, R.-I.-G., & Florea, A. (2020). Software application for organizational sustainability performance assessment. Sustainability, 12(11), 4435. https://doi.org/10.3390/su12114435

[70] Hanif, E., Hashemnejad, H., & Ghafourian, M. (2017). The concept of sustainable dwelling epitomized in the courtyards of Iranian houses: A case study of houses in Kashan in the Qajar Period. https://philpapers.org/rec/HANTCO-50

[71] Haseli, G., Nazarian-Jashnabadi, J., Shirazi, B., Hajiaghaei-Keshteli, M., & Moslem, S. (2024). Sustainable strategies based on the social responsibility of the beverage industry companies for the circular supply chain. Engineering Applications of Artificial Intelligence, 133, 108253. https://doi.org/10.1016/j.engappai.2024.108253

[72] Costa, J. T., & do Nascimento, R. P. C. (2023). ICT Governance Practices and Industry 4.0 Technologies in Support of Decision-Making in Brazilian Smart Cities in the Face of the COVID-19 Pandemic. IEEE Transactions on Computational Social Systems. https://doi.org/10.1109/TCSS.2023.3306707

[73] Nazarian-Jashnabadi, J., Haseli, G., & Tomaskova, H. (2024). Digital transformation for the sustainable development of business intelligence goals. In Decision Support Systems for Sustainable Computing (pp. 169–186). Elsevier. https://doi.org/10.1016/B978-0-443-23597-9.00008-1

[74] Attanasio, A., Cerquitelli, T., & Chiusano, S. (2016). Supporting the analysis of urban data through NoSQL technologies. 2016 7th International Conference on Information, Intelligence, Systems & Applications (IISA), 1–6. https://doi.org/10.1109/IISA.2016.7785334

[75] Manesh, M. M., & Nabavi, E. T. (n.d.). Using System Dynamics to Scrutinize Behavioral Feedback Loops in Groundwater Management. Retrieved October 21, 2024. https://www.researchgate.net/profile/Mehdi-Moghadam-Manesh/publication

[76] Rezazadeh, J., Bagheri, R., Karimi, S., Nazarian-Jashnabadi, J., & Nezhad, M. Z. (2023). Examining the impact of product innovation and pricing capability on the international performance of exporting companies with the mediating role of competitive advantage for analysis and decision making. Journal of Operations Intelligence, 1(1), 30–43. https://doi.org/10.31181/jopi1120232

[77] Kazemi, A., Kazemi, Z., Heshmat, H., Nazarian-Jashnabadi, J., & Tomášková, H. (2024). Ranking factors affecting sustainable competitive advantage from the business intelligence perspective: Using content analysis and F-TOPSIS. Journal of Soft Computing and Decision Analytics, 2(1), 39–53. http://dx.doi.org/10.31181/jscda21202430

[78] Haseli, G., & Sheikh, R. (2022). Base criterion method (BCM). In Multiple criteria decision making: Techniques, Analysis and Applications (pp. 17–38). Springer. https://doi.org/10.1007/978-981-16-7414-3_2

[79] Nazarian-Jashnabadi, J., Ronaghi, M., alimohammadlu, M., & Ebrahimi, A. (2023). The framework of factors affecting the maturity of business intelligence. Business Intelligence Management Studies, 12(46), 1-39. https://doi.org/10.22054/ims.2023.74305.2346

[80] Haseli, G., Sheikh, R., & Sana, S. S. (2020). Base-criterion on multi-criteria decision-making method and its applications. International Journal of Management Science and Engineering Management, 15(2), 79–88. https://doi.org/10.1080/17509653.2019.1633964

[81] Farahani, S. D., Abadeh, A., Alizadeh, A., & Helforoush, Z. (2024). Artificial intelligence-based prediction of heat transfer enhancement in ferrofluid flow under a rotating magnetic field: Experimental study. Case Studies in Thermal Engineering, 58, 104442. https://doi.org/10.1016/j.csite.2024.104442

[82] Dong, L., & Zhang, M. (2023). Commercial bank data asset quality evaluation model based on fermatean fuzzy TOPSIS. Procedia Computer Science, 221, 565–572. https://doi.org/10.1016/j.procs.2023.08.023

[83] Haseli, G., Ranjbarzadeh, R., Hajiaghaei-Keshteli, M., Ghoushchi, S. J., Hasani, A., Deveci, M., & Ding, W. (2023). HECON: Weight assessment of the product loyalty criteria considering the customer decision's halo effect using the convolutional neural networks. Information Sciences, 623, 184–205. https://doi.org/10.1016/j.ins.2022.12.027

[84] Jashnabadi, J. N., Pooya, A., & Bagheri, R. (2023). Provide a model for budget policy in university-community communication programs with a system dynamics approach (case study: Ferdowsi University of Mashhad). J. Ind. Manag. Perspect, 13(1), 9–39. https://doi.org/10.48308/jimp.13.1.9
[85] Amiri Sardari, Z., Abdoli Mohamadabadi, T., Nazarian-Jashnabadi, J., Tesoriere, G., & Campisi, T. (2024). Smart Experience and Green Health Tourism: The Moderating Role of Content Marketing. Sustainability, 16(11), 4546. https://doi.org/10.3390/su16114546