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Adoption of energy consumption in urban mobility considering digital carbon footprint: A two-phase interval-valued Fermatean fuzzy dominance methodology

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ABSTRACT

Interval-valued Fermatean fuzzy sets play a significant role in modelling decision-making problems with incomplete information more accurately than intuitionistic fuzzy sets. Various decision-making methods have been introduced for the different classes IFSs. In this study, we aim to introduce a novel two-phase interval-valued Fermatean fuzzy dominance method which suits the decision-making problems modelled under the IVFFS environment well and study its applications in the adoption of energy consumption in Urban mobility considering digital carbon footprint. The proposed method considers the importance and performance of one alternative with respect to all others, which is not the case with many available decision-making algorithms introduced in the literature. Transportation is one of the most significant sources of global greenhouse gas (GHG) emissions. Numerous potential remedies are proposed to reduce the quantity of GHG generated by transportation activities, including regulatory measures and public transit digitalization initiatives. Decision-makers, however, should consider the digital carbon footprint of such projects. This study proposes three alternatives for reducing GHG emissions from transportation activities: incremental adoption of digital technologies to reduce energy consumption and greenhouse gases, disruptive digitalization technologies in urban mobility, and redesign of urban mobility using regulatory approaches and economic instruments. The proposed novel two-phase interval-valued Fermatean fuzzy dominance method will be utilized to rank these alternative projects in order of advantage. First, the problem is converted into a multi-criterion group decision-making problem. Then a novel two-phase interval-valued Fermatean fuzzy dominance method is designed and developed to rank the alternatives. The importance and advantage of the proposed two-phase method over other existing methods are discussed by using sensitivity and comparative analysis. The results indicate that rethinking urban mobility through governmental policies and economic tools is the least advantageous choice, while incremental adoption of digital technologies is the most advantageous.

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1. Introduction

A significant portion of the total greenhouse gas (GHG) emissions worldwide are caused by the transportation sector. According to figures from the US Environmental Protection Agency, transportation-related activities are responsible for 27% of all GHG emissions in the US in 2020 (EPA, 2022). The same is true for nations throughout Europe. According to the European Commission, transportation-related activities are responsible for 25% of the GHG emissions produced in Europe, and 70% of these activities are connected to road transport (EC, 2016). Therefore, adopting energy consumption and GHG emission reduction strategies is more than important to lessen the impact of urban transportation on climate change due to its high GHG emissions.

Numerous digitalization initiatives have been implemented in transportation systems that are effective in raising system sustainability, including improving the appeal of bike-sharing, car-sharing, and micro-mobility options and incorporating digitalization in public transit (Abduljabbar et al., 2021; McQueen et al., 2021). However, the type of implementation, such as gradual or disruptive, matters in terms of the scope of benefits and drawbacks that the application will provide. In addition to incremental and disruptive digitalization of transportation networks, regulatory measures and economic instruments are other possibilities for boosting the system's sustainability. Fuel and carbon taxes, as well as fuel quality standards and GHG emission performance standards, are only a few of the many useful applications (May et al., 2006; Shahid et al., 2014).

Around the world, authorities and decision-makers are looking for solutions to reduce the GHG emissions associated with transportation-related activities. This study provides three different alternative implementation strategies in this direction: using disruptive digitalization technologies in urban mobility to reduce energy consumption and greenhouse gases and redesigning urban mobility through regulatory approaches and economic instruments. The incremental adoption of digital technologies in urban mobility is intended to reduce energy consumption and greenhouse gas emissions. These alternatives are advantages prioritized using the proposed multi-criteria decision-making (MCDM) approach. The options and criteria for this investigation were chosen through a thorough examination of the relevant literature. A questionnaire is created using the alternatives and the criteria, asking each alternative to be evaluated against each criterion. Experts with experience in the topic of this study are surveyed using this questionnaire, and their responses are utilized in the proposed MCDM approach. A case study is developed so that the experts can have a foundation upon which to stand while responding to the questions.

1.1. The objective of this study

This study has the potential to be used as a guide by transportation system authorities as they examine a transition to a more sustainable urban transportation system. Additionally, the adaptability of this study increases its applicability, as each country has different transportation system dynamics and cultural differences. Therefore, it is advantageous to modify the study's alternatives and criteria and use the same MCDM approach with the modified alternatives and criteria.

1.2. The motivation for using two-phase interval-valued Fermatean fuzzy dominance method

Various methods are available in the literature for solving a multi-criteria group decision-making problem. Fuzzy and intuitionistic fuzzy based group MCDM methods are introduced in the literature to handle group MCDM problems with imprecise and incomplete information. Each of those methods has its own advantages and disadvantages concerning the other available methods. However, they use different ideas in every method. Ranking of intuitionistic fuzzy numbers (various classes of intuitionistic fuzzy numbers) plays a major role in solving any decision-making problems modelled using a specific class of intuitionistic fuzzy numbers. Especially the ranking of interval-valued Fermatean fuzzy numbers will play a major role in any decision-making method if the problem is modelled under the IVFFN environment. However, most of the available MCDM methods available in the literature use 'partial order ranking principles', which is a drawback of existing methods. In this paper, we introduce a novel decision-making method for solving a decision problem modelled using IVFFNs which utilizes the total ordering principle on the set of IVFFNs. In this study, we aim to introduce a new method for solving multi-criteria group decision-making problems that consider the relative importance of the performance of one specific alternative with respect to all other alternatives available in the MCDM problem, which also makes the proposed method differs from the other MCDM methods available for various classes of fuzzy sets. The proposed method considers two phases. In the first phase (Phase I), we find the normalized weights of all the sub-criteria present in the given group decision-making problem. Then in the second phase (Phase II), we use the idea of dominance relation to find the relative performance of one specific alternative with respect to the performance of other alternatives, and we solve a case problem modelled under an interval-valued Fermatean fuzzy environment. In Phase II, we mainly use the ranking method for comparing arbitrary interval-valued Fermatean fuzzy numbers (IVFFNs) in the aggregated performance matrix and by using this, we calculate the entire dominance degree. The ranking of IVFFNs plays an important role in this proposed Two-Phase interval-valued Fermatean fuzzy dominance method (TPIVFFDM). The concept of Fermatean fuzzy sets (Senapati and Yager, 2019) was introduced in the literature as a generalization to intuitionistic fuzzy sets and Pythagorean fuzzy sets. Later, interval-valued Fermatean fuzzy sets (IVFFS) were introduced by Jeevaraj (2021) as a generalized to the idea of Fermatean fuzzy sets and he has defined few basic operations and studied various Mathematical aspects of IVFFNs by establishing various theorems and propositions. Jeevaraj (2021) has introduced four score functions for comparing any two arbitrary IVFFNs. Then he has proposed a new ordering principle (that defines total order on the class of IVFFNs) by using the proposed score functions. In 2022, Rani and Mishra (2022) introduced two score functions, namely, score and accuracy of IVFFNs and tried to compare any two arbitrary IVFFNs. However, the ranking principle proposed by Rani and Mishra (2022) was not efficient in ranking arbitrary IVFFNs, which was identified by Rani et al. (2022) on the same year. Rani et al. (2022) introduced a new ranking principle for comparing IVFFNs. They have considered four score functions for their ranking principle. They have taken two score functions from Rani and Mishra's (2022) work, one score function from Jeevaraj (2021), and finally, they have introduced one score function namely the modified score function. The ranking principle introduced by Rani et al. (2022) overcomes the drawback of Rani and Mishra's (2022) ranking principle. Unfortunately, Rani et al.'s (2022) method also fails to discriminate arbitrary IVFFNs. In this paper, after introducing the TPIVFFDM, we use an illustrative example to study the importance of using a 'total ordering' ranking principle (Jeevaraj, 2021) in the calculations of TPIVFFDM.

2. Literature review

Numerous studies in the extant literature examined the benefits and drawbacks of gradual and disruptive digitalization implementations in transportation systems and the impact of using regulatory measures and economic policies.

Various studies have found that disruptive digitization in transportation networks is inefficient, while others have found that a disruptive implementation leaves consumers with no choice but to adapt. In a separate study, the actual implementations of private vehicle restrictions in twelve major cities are examined (Poudenx, 2008). It is claimed that regulations restricting private vehicle use direct people to use public transit. However, these rules are inefficient because individuals choose to travel in comfort rather than as part of a more sustainable system. As a result, this study demonstrates one of the reasons why disruptive adoptions in transportation systems may fail. However, studies show that disruptive applications are required to provide a strong transition to more sustainable systems. For example, according to a prior study, the penetration rate of electric vehicles is below the required level for broad market acceptance (Berkeley et al., 2017). The adoption of electric vehicles has been primarily driven by incremental applications such as incentives, according to the report, although the penetration rate remains below the required level. As a result, the installation of fuel-driven car prohibitive regulations, while disruptive, can increase the level of electric vehicle usage to the desired level.

The management of transportation systems also has a choice between gradual applications, which have benefits and drawbacks, and disruptive deployments. According to a different study, there are several benefits to incrementally implementing digitalization in transportation systems, including allowing for the necessary time to develop enabling policies, being able to get a lot more people to use the adopted service, and expanding the implementation area (Hitge and Van Dijk, 2012). The application of metaverse technology to traffic management strategies is another illustration of progressive digitization in transportation systems (Pamucar et al., 2022). The incremental transition is more likely since a disruptive shift to metaverse-aided traffic control is not imminent. Although the primary goal of traffic management techniques is to regulate traffic and vehicle speeds and so reduce GHG emissions, blockchain is a technology that emits a large amount of GHGs (Sedlmeir et al., 2020; Othman et al., 2019). As a result, it would be unwise to implement metaverse-assisted traffic management gradually because it could result in a rise in the transportation system's carbon footprint.

Using regulatory strategies and economic tools is another viable solution to reducing GHG emissions associated with transportation-related activities and incremental and disruptive digitalization in transportation systems. In a different study, the impacts of increasing fuel and car purchase taxes on household-level private transportation utilization are examined using a prediction model (Liu and Cirillo, 2015). The study's findings indicate that household-level private transportation usage is subject to both taxing schemes, however, the application of fuel taxes resulted in a bigger improvement in the methods of reducing GHG emissions. Fuel and car purchase taxes may appear to be solutions for lowering GHG emissions. However, there are drawbacks and challenges in implementing these policies. According to a different study, implementing fuel taxes is one of the greatest strategies to cut fuel consumption, but doing so puts a lot of political pressure on the government and makes these policies less likely to be implemented (Hammar et al., 2004).

Nayagam et al. (2017) proposed a new MCDM algorithm for solving decision problems under interval-valued intuitionistic fuzzy environment. Also, they demonstrated the applicability/practicality of the proposed intuitionistic fuzzy MCDM problem using an illustrative example. Güneri and Deveci (2023) used q-rung orthopair fuzzy-based decision models for evaluating the selection criteria of supplier companies operating in the defence industry. The study constructed supplier selection criteria through a detailed analysis of numerous studies conducted between 1966 and 2019. Bouraima et al. (2023) ranked regional transport infrastructure programmes using fuzzy Step-Wise Weight Assessment Ratio Analysis based on the fuzzy Bonferroni aggregator. Önden et al. (2023) introduce a new fuzzy Einstein norms-based decision-making model for ranking the best alternative from the sixteen alternatives evaluated based on their performance under 8 criteria. Pamucar et al. Pamučar et al. (2023) proposed an Aczel–Alsina aggregation operator on the class fuzzy rough numbers and showed the applicability of the proposed aggregation operator in selecting the best healthcare waste management treatment. Ranking principles and aggregation operators on various classes of intuitionistic fuzzy sets are introduced, and their applications in various domains have been reported (Alrasheedi and Jeevaraj, 2023; Jeevaraj et al., 2023; Jeevaraj, 2022; Selvaraj et al., 2022). Different generalizations of Fermatean fuzzy sets have been introduced, and also their applications have been studied in recent years (Broumi et al., 2023, 2022; Ali et al., 2023; Narang et al., 2023; Ejegwa and Zuakwagh, 2022; Palanikumar et al., 2023; Mishra et al., 2023; Akram et al., 2021; Rasoulzadeh et al., 2022). Majumdar et al. (2021) discussed the idea of trapezoidal fuzzy TOPSIS method and discussed its applicability in the selection of resilient suppliers in manufacturing industries in the post COVID-19 scenario. (Selvaraj and Majumdar, 2021) have proposed a novel ranking method on the set of IVIFNs, studied its Mathematical properties and discussed the effectiveness of the proposed novel score function in comparison with the other familiar ranking methods on the set of IVIFNs. This study differs from the earlier studies in the literature in that it uses a novel MCDM method to rank various alternatives according to their perceived benefits. Authorities and decision-makers that are seeking strategies to cut energy usage and GHG emissions in a transportation system may find the study's findings insightful and practical. In this paper,

- We propose a novel Two-Phase interval-valued Fermatean fuzzy Dominance method (TPIVFFDM) for solving a multi-criteria group decision-making problem modelled using IVFFNs.
- The proposed TPIVFFDM algorithm considers the relative importance of each alternative concerning all the remaining alternatives based on their performance with respect to different criteria.
- In order to show the applicability of the proposed TPIVFFDM algorithm, we have considered a real case study problem and solved it using TPIVFFDM.
- Sensitivity Analysis is very much important for any algorithm, and we have done it properly by considering different scenarios, which can be seen in Section 5.2.
- IVFFNs have been introduced in the literature recently, and introducing various MCDM algorithms for solving real-life problems is essential. The proposed TPIVFFDM considers the total ordering principle for ranking, which makes the algorithm more robust when it is compared with the familiar MCDM methods (for problems modelled under interval-valued Fermatean fuzzy environment) available in the literature. This can be seen in Section 5.3.

3. Problem definition

There are several ways to deal with climate change and rising greenhouse gas emissions. These solutions can be applied both locally and globally. A clean future can be obtained through both individual and social behaviour in climate change-related activities (such as reducing carbon footprint and increasing energy efficiency). This is feasible by emphasizing digital technology in urban mobility, transitioning to digital technologies, passing laws and providing economic incentives to managers, etc. However, deciding how to implement the transition to digital technology is also necessary. Transitions, both incremental and disruptive, offer advantages and costs. As a result, an advantage analysis should be performed to decide which is more appropriate.

Improving transportation activities, which is one of the fields with the highest energy use, can help to minimize energy consumption. Instead of people preferring individual mobility, economic incentives or by-laws might boost the usage of public transit. Increasing the use of public transportation can both directly and indirectly reduce greenhouse gas emissions. As a result, three distinct alternatives have been identified in this study to reduce energy consumption and greenhouse gas emissions in urban mobility while accounting for the digital carbon footprint. The thirteen separate criteria were developed to evaluate these three different alternatives.

3.1. Definition of alternatives

A_1*: Incremental adoption of digital technologies in urban mobility for Reducing Energy Consumption and Greenhouse Gases (GHGs):* Climate change and the growth in greenhouse gas emissions are two of the most serious threats to the world's future. There are ways to reduce greenhouse gas emissions, such as expanding digitization in public transportation and implementing novel incremental technologies in urban mobility. By implementing these ideas, we can create a more ecologically friendly and sustainable world by lowering energy usage and greenhouse gas emissions (Shaheen and Lipman, 2007).

A_2*: Using disruptive digitalization technologies in urban mobility for Reducing Energy Consumption and Greenhouse Gases (GHGs):* Digital technology is vital in the emergence of novel applications in urban mobility. Where the environmental impact is minor, the outcomes of disruptive solutions may be limited. Because these solutions contain more advanced technology elements that are acceptable, the outcomes can be both direct and indirect. Disruptive digitalization technologies can include replacing existing public transportation systems with smart, environmentally friendly, and autonomous systems (Dia et al., 2020).

A_3*: Redesign of urban mobility through regulatory approaches and economic instruments:* Another major technique to combat greenhouse gas emissions and the energy consumption is urban mobility, which can be accomplished through regulatory approaches and economic tools. People can minimize their involvement in private vehicle usage by implementing fuel and carbon taxation, road tolls, and congestion pricing to eliminate wasteful and excessive energy consumption. Furthermore, it can provide financial incentives for managers to adopt green technologies. People may switch to electric vehicles if the vehicle tax is reduced or eliminated while purchasing them (Spickermann et al., 2014).

3.2. Definition of criteria

The thirteen evaluation criteria under four aspects are defined as follows:

(1) Digital Carbon Footprint Awareness Aspect

C_1 : *Increased awareness of the personal impact on digital carbon footprint (Benefit):* Personal awareness is critical in addressing climate change and rising greenhouse gas emissions. Each individual may help to ensure a clean future by reducing their carbon footprint. Using public transportation instead of personal vehicles, caring for energy efficiency at home, and engaging in micromobility activities such as car sharing, for example, all help to lessen the carbon footprint (Edstrand, 2016).

C_2 : *Lack of involvement, diversity, and inclusion; aligned measurements and goals (Cost):* Companies may not embrace initiatives that minimize energy use and move to environmentally friendly technologies unless they are mandated. Institutions probably will not participate in environmental initiatives due to factors such as a lack of economic incentives (Luthra et al., 2016).

C_3 : *Enabling greener choices through awareness (Benefit):* Greenhouse gas emissions can be reduced by encouraging individuals to engage in ecologically friendly and sustainable activities. Examples include employing micromobility applications such as bicycles instead of driving a car, purchasing recyclable items, and using technical equipment that uses renewable energy sources (Abduljabbar et al., 2021).

(2) Environmental and Health Aspect

C_4 : *Emission reduction (Benefit):* The consequences of climate change can be mitigated in the medium and long term by reducing greenhouse gas emissions. The future of the planet can be improved by pressuring to cut their CO2 emissions by taking significant action at conferences (like the Paris Conference) sometimes conducted with the participation of the vast majority of nations (Falkner, 2016).

C_5 : *Improved mental health and wellness (Benefit):* In addition to offering solely physical contributions, people's strong and fit mental health can also play an essential part in lowering the carbon footprint. Making a positive association between people's economic power and their carbon footprint may be incorrect. Local improvements in entertainment, health, and education sectors may motivate people to avoid unnecessary travel (Seligman et al., 1978).

(3) Efficiency and Sustainability Aspect

C_6 : *Challenges with energy storage and low-carbon fuel energy density (Cost):* Renewable and nonrenewable energy sources can both provide energy needs. The energies supplied by these sources are spent in an instant. These energies can be used later via energy storage. However, because technology advancements are insufficient, there may be issues with energy storage. Furthermore, greenhouse gas emissions can be lowered by switching to low-carbon fuels that emit fewer greenhouse gases. However, their implementation may not be favoured because it incurs additional costs (Dodds and Garvey, 2016).

C_7 : *Need for accelerating the energy transition (Cost):* The cost of replacing nonrenewable energy sources like gasoline, coal, and natural gas with renewable energy sources like the sun, water, and wind is expensive. Accelerating this transition process with additional expenses and manpower is also possible (De La Peña et al., 2022).

C_8 : *Allowing for a better balance between proximity and mobility (Benefit):* A healthy mix of proximity and mobility can help make daily activities more ecologically friendly, sustainable, and efficient. This, together with improved balance, can help to reduce energy expenditure in daily tasks (Dadashpoor and Rostami, 2017).

C_9 : *Providing sustainable accessibility (Benefit):* Sustainability is a requirement in all aspects of life. Any sector in our daily lives that is sustainable can help to reduce both energy use and efficiency. Achieving sustainable accessibility can help to minimize greenhouse gas emissions while also improving energy use (Curtis, 2008).

(4) Management Aspect

C_{10} : *The managing capability of climate transition risks (Benefit):* Climate change is one of the major threats to the world's future. Climate change, migration, wars, increased forest fires, and other factors are expected. Managing the hazards that are projected to arise as a result of climate change can help both nature and humanity in the long run (Pelling, 2010).

C_{11} : *With good data and tools, organizations augment their ability to make faster, more effective decisions (Benefit):* Managers may make better decisions faster if they keep data on past, present, and future events on a frequent and efficient basis. Environmental issues, such as climate change, which threatens the world's future, can be addressed more sustainably through quick and efficient decision-making (Aftab and Siddiqui, 2018).

C_{12} : *An improved organization and management of public space (shared modes, public transport becomes the fastest) (Benefit):* Managers can make facilities such as public spaces, transit, and micromobility applications more environmentally friendly, rapid, sustainable, and efficient. Improvements in traffic management, for example, can enhance the usage of both mass transportation and micromobility applications. This increase is projected to result in a direct decrease in energy use (Fan and Harper, 2022).

C_{13} : *Increased need for interoperability, longevity and security (Cost):* The internet has shown the value of redundancy in terms of resilience, with various options that prevent reliance on single routes or hubs. The rise of environmentally friendly revolutionary technologies may necessitate that these technologies work in tandem. It is also critical that these technologies are long-lasting and safe. If these parameters are met, an ecologically friendly system with more sustainable energy management can be constructed. However, it is possible to reach them if extra costs are paid (Granjal et al., 2013).

3.3. Basic mathematical definitions

Here we see some basic Mathematical definitions.

Definition 3.3.1 (*Jeevaraj, 2021*). Let us consider the collection of all closed sub-intervals of the unit interval and denote it as $E[0,1]$. Then, an interval-valued Fermatean fuzzy set (IVFFS) on any universal set $X \neq \phi$ is defined as $F_I = \left\{ \left\langle x, \mu_{F_I}(x), \nu_{F_I}(x) \right\rangle : x \in X \right\}$ where $\mu_{F_I} : X \to E[0,1], \nu_{F_I} : X \to E[0,1]$ with $0 < sup_x(\mu_{F_I}(x))^3 + sup_x(\nu_{F_I}(x))^3 \leq 1$.

Also, for each $x \in X$, $\mu_F(x)$ and $\nu_F(x)$ are closed intervals and $\mu_{F_L}(x)$, $\mu_{F_U}(x)$ and $\nu_{F_L}(x)$, $\nu_{F_U}(x)$ are their lower and upper bounds of membership and non-membership functions. Thus, any IVFFS F can be represented as follows:

$$F = \left\{ \left\langle x, [\mu_{F_L}(x), \mu_{F_U}(x)], [\nu_{F_L}(x), \nu_{F_U}(x)] \right\rangle : x \in X \right\}$$
$$with\ 0 < (\mu_{F_U}(x))^3 + (\nu_{F_U}(x))^3 \leq 1.$$

For each element $x \in X$, we can calculate the degree of hesitancy $\pi_F(x)$ to F as $\pi_F(x) = [\pi_{F_L}(x), \pi_{F_U}(x)] = [\sqrt[3]{1 - (\mu_{F_U}(x))^3 - (\nu_{F_U}(x))^3}, \sqrt[3]{1 - (\mu_{F_L}(x))^3 - (\nu_{F_L}(x))^3}]$.

Any IVFFN is denoted by $F = ([\mu_{F_L}, \mu_{F_U}], [\nu_{F_L}, \nu_{F_U}])$ for convenience. It can be seen that IVFFS reduces to FFS when the boundaries are the same. That is, if $\mu_{F_L} = \mu_{F_U}$ and $\nu_{F_L} = \nu_{F_U}$, then any IVFFS coincides with FFS.

Definition 3.3.2 (Jeevaraj, 2021). Let $F_1 = \left\langle [\mu_{F_{1L}}, \mu_{F_{1U}}], [\nu_{F_{1L}}, \nu_{F_{1U}}] \right\rangle \in IVFFN$. Then the membership score J_M of F_1 is defined as

$$J_M(F_1) = \frac{\mu^3_{F_{1L}} + \mu^3_{F_{1U}} - \nu^3_{F_{1L}} - \nu^3_{F_{1U}}}{2} \tag{3.1}$$

The Hesitancy-score J_H of F_1 is defined as

$$J_H(F_1) = \frac{\mu^3_{F_{1L}} + \mu^3_{F_{1U}} + \nu^3_{F_{1L}} + \nu^3_{F_{1U}}}{2} \tag{3.2}$$

The Precise-score of F_1 is defined as

$$J_P(F_1) = \frac{-\mu^3_{F_{1L}} + \mu^3_{F_{1U}} + \nu^3_{F_{1L}} - \nu^3_{F_{1U}}}{2} \tag{3.3}$$

The complete-score of F_1 is defined as

$$J_C(F_1) = \frac{-\mu^3_{F_{1L}} + \mu^3_{F_{1U}} - \nu^3_{F_{1L}} + \nu^3_{F_{1U}}}{2} \tag{3.4}$$

Definition 3.3.3 (*Total ordering principle: Jeevaraj, 2021*). Let $F_1 = ([\mu_{F_{1L}}, \mu_{F_{1U}}], [\nu_{F_{1L}}, \nu_{F_{1U}}]), F_2 = ([\mu_{F_{2L}}, \mu_{F_{2U}}], [\nu_{F_{2L}}, \nu_{F_{2U}}]) \in IVFFN$. Let $J_M(F_i), J_H(F_i), J_P(F_i)$ and $J_C(F_i)$ be the 4 score functions (defined in Definition 3.3.2) for two IVFFNs (F_1, F_2). Then the ranking (total order) principle for discriminating any two arbitrary IVFFNs is defined as follows,

- If $J_M(F_1) < J_M(F_2)$ then $F_1 < F_2$
- If $J_M(F_1) > J_M(F_2)$ then $F_1 > F_2$
- If $J_M(F_1) = J_M(F_2)$ then
  - If $J_H(F_1) < J_H(F_2)$ then $F_1 < F_2$
  - If $J_H(F_1) > J_H(F_2)$ then $F_1 > F_2$
  - If $J_H(F_1) = J_H(F_2)$ then
    - If $J_P(F_1) > J_P(F_2)$ then $F_1 < F_2$
    - If $J_P(F_1) < J_P(F_2)$ then $F_1 > F_2$
    - If $J_P(F_1) = J_P(F_2)$ then
      - If $J_C(F_1) < J_C(F_2)$ then $F_1 < F_2$
      - If $J_C(F_1) > J_C(F_2)$ then $F_1 > F_2$
      - If $J_C(F_1) = J_C(F_2)$ then $F_1 = F_2$

4. Proposed methodology

In this section, we introduce the idea of a Two-Phase interval-valued Fermatean fuzzy Dominance method (TPIVFFDM) for solving a multi-criteria group decision-making problem.

In this method, the dominance relation relies on the ranking of data. In recent years, the other generalizations of IFNs, such as Pythagorean fuzzy numbers, Fermatean fuzzy numbers, interval-valued Pythagorean fuzzy numbers, and interval-valued Fermatean fuzzy numbers, are used in the literature due to their flexibility in handling imprecision, and incompleteness occurs in the data. This section considers interval-valued Fermatean fuzzy numbers for modelling a multi-criteria group decision-making problem. IVFFNs are used here since it is the real generalization of IVPFNs, PFNs, IVIFNs, and IFNs. Also, we have used the total ordering principle on the set of IVFFNs for ranking, which makes the proposed method different from the other familiar decision-making methods available in the literature. In this study, initially, we did a literature survey to identify the factors which affect the performance adoption of energy consumption in urban mobility by considering the DCF. Then we discuss with the group of six experts who have great experience in reducing the irrelevant criteria and obtaining a reasonable number of criteria affecting the energy consumption adoption. Experts have given their ratings in the form of linguistic terms.

4.1. *Algorithm for solving an interval-valued fermatean fuzzy multi-criteria group decision-making problem*

Any multi-criteria group decision-making problem can be defined mathematically as follows,

Let $E = \{E_1, E_2, E_3, \dots, E_r\}$ be the group of r decision-makers (Experts) who will evaluate the set of l Alternatives denoted by A and defined as $A = \{A_1, A_2, \dots, A_l\}$ based on their performance with respect to n_1 criteria represented by a set $C_{GDM} = \{C_1, C_2, \dots, C_{n_1}\}$. Also, we consider K be the set containing weights of all n_1 criteria. It is defined as $K = \{K_1, K_2, \dots, K_{n_1}\}$ where each K_i represents the weight of criteria C_i. We call any multi-criteria group decision-making problem as an interval-valued Fermatean fuzzy multi-criteria group decision-making (IVFFMCGDM) problem when the performance of alternatives based on various criteria is evaluated using IVFFNs. In this paper, we use IVFFNs for modelling the performance of alternatives, relative importance, and weights of various criteria. The main aim of this subsection is to solve the IVFFMCGDM problem using dominance relation.

The proposed methodology is composed of two main phases. In the first phase (Phase I), we calculate the normalized weights of all the sub-criteria available in any (given) group decision-making problem. Then, in the second phase (Phase II), we use the idea of dominance relation for solving an IVFFMCGDM.

Algorithm 4.1: Two-Phase Interval-valued Fermatean fuzzy Dominance Method (Algorithm for solving an IVFFMCGDM problem)

Phase I: Finding the normalized weights of all the sub-criteria by considering main criteria final weights

A step-by-step procedure of Phase I is given below,

Phase I: Finding the weights for all the sub-criteria

1. **Formation of Decision Matrix modelled under interval-valued Fermatean fuzzy environment:**
   It involves the following two sub-steps.
   (a) the 'r' Experts (decision-makers) provide their opinion about the importance of various 'n' main criteria using the linguistic terms (9-point scale) provided in Table 3.
   (b) Then, all these 9-point scale linguistic terms are converted in the form of IVFFNs using the IVFFN equivalent values given in Table 3. It is represented by an '$r \times n$' matrix denoted by $MC = (mc_{ij})_{n \times r}$ where each m_{ij} represents the importance of 'i'-th main criteria given by 'j'-th expert (decision-maker). Also, each $m_{ij} = ([p_{ij}, q_{ij}], [r_{ij}, s_{ij}])$ is represented in the form of an IVFFN.

2. **Calculating the aggregated importance and final weights of all the main criteria:**
(a) The aggregated importance of all the 'n' main criteria is denoted by M_i, where $i = 1, 2, \dots, n$ and obtained by using the following formula,
$$M_i = \left(\left[\sum_{j=1}^{r} \frac{p_{ij}}{r}, \sum_{j=1}^{r} \frac{q_{ij}}{r} \right], \left[\sum_{j=1}^{r} \frac{r_{ij}}{r}, \sum_{j=1}^{r} \frac{s_{ij}}{r} \right] \right) \tag{4.1}$$
(b) The final weight of all the 'n' main criteria is denoted by W_i, where $i = 1, 2, \dots, n$ and obtained by using the following formula
$$W_i = \frac{J_M(M_i)}{\sum_{i=1}^{n} J_M(M_i)} \tag{4.2}$$
3. **Calculating the aggregated importance and final weights of all the sub-criteria:**
In the considered 'group decision-making (GDM)' problem, we have 'n_1' sub-criteria associated with 'n' main criteria. The expert's ('r' decision-makers) opinion about the relative importance of each sub-criteria with respect to each main criterion is represented by an '$n_1 \times r$' matrix. It is denoted as $S = (s_{ij})_{n_1 \times r}$, where each $s_{ij} = ([u_{ij}, v_{ij}], [w_{ij}, x_{ij}])$ is an IVFFN and $j = 1, 2, \dots, r; i = 1, 2, \dots, n_1$. Here, we give the following steps to calculate the weights of all the sub-criteria.
(a) The aggregated importance of all the 'n_1' sub-criteria is denoted by S_i, where $i = 1, 2, \dots, n_1$ and obtained by using the following formula,
$$S_i = \left(\left[\sum_{j=1}^{r} \frac{u_{ij}}{r}, \sum_{j=1}^{r} \frac{v_{ij}}{r} \right], \left[\sum_{j=1}^{r} \frac{w_{ij}}{r}, \sum_{j=1}^{r} \frac{x_{ij}}{r} \right] \right) \tag{4.3}$$
(b) The final weight of all the 'n_1' sub-criteria is denoted by $W_{i'}$, where $i = 1, 2, \dots, n$ and obtained by using the following formula
$$W_{i'} = \frac{J_M(S_i)}{\sum_{i=1}^{n} J_M(S_i)} \tag{4.4}$$
.
4. **Normalized final weights calculation of all sub-criteria by considering main criteria final weights:**
The final weights of all the sub-criteria W_i'' (where $i = 1, 2, \dots, n_1$) by considering main criteria final weights (W_i) and sub-criteria weights ($W_{i'}$)is obtained by multiplying the sub-criteria weight $W_{i'}$ with the weights (W_i) of the corresponding main criteria. Then the normalized final weights of all the sub-criteria $K(C_i)$ (where $i = 1, 2, \dots, n_1$) by considering main criteria final weights (W_i) and sub-criteria weights ($W_{i'}$) is calculated using the formula,
$$K(C_i) = \frac{W_i''}{\sum_{i=1}^{n_1} W_i''} \tag{4.5}$$
.

Phase II: Solving group decision-making problem using Dominance relation

A step by step procedure of Phase II is given below,

1. **Formation of Decision Matrix modelled using IVFFNs (for the considered GDM problem):**
It involves with two sub-steps.
(a) the 'r' Decision-makers provide their opinion about performance of 'l' alternatives with respect to 'n_1' criteria using the 9-point linguistic terms provided in Table 3.
(b) Then, each of these 9 linguistic terms is converted into IVFFNs using the IVFFN equivalent values provided in Table 3. It is represented by an '$1 \times r$' matrix denoted by $R = (A^k)_{1\times r}$, where each $A^k = (a^k_{ij})_{l\times n_1}, i = 1, 2, \dots, l; j = 1, 2, \dots, n_1; k = 1, 2, \dots, r$ is the '$l \times n_1$' matrix represents the kth expert's (decision-maker's) opinion about the performances of 'l' alternatives with respect to 'n_1' criteria. Also, each $a^k_{ij} = ([p^k_{ij}, q^k_{ij}], [r^k_{ij}, s^k_{ij}])$ is represented by an IVFFN.
Note: At the end of step 1, we will have r number of $l \times n_1$ matrix in a considered IVFFMCGDM problem which is represented by R, a '$1 \times r$' row matrix.
2. **Calculating the aggregated performance of all the alternatives with respect to various criteria:**
The aggregated performance of all the 'l' alternatives with respect to 'n_1' criteria based on all the 'r' decision-makers is denoted by $D = (d_{ij})_{l\times n_1}$, where $j = 1, 2, \dots, n_1; i = 1, 2, \dots, l$ and each d_{ij} is obtained by using the following formula,
$$d_{ij} = \left(\left[\sum_{k=1}^{r} \frac{p^k_{ij}}{r}, \sum_{k=1}^{r} \frac{q^k_{ij}}{r} \right], \left[\sum_{k=1}^{r} \frac{r^k_{ij}}{r}, \sum_{k=1}^{r} \frac{s^k_{ij}}{r} \right] \right) \tag{4.6}$$
.
Note: At the end of step 2, from the row matrix R, we will get a single '$1 \times r$' matrix which is represented by D. All the calculations are going to be performed on D.
3. **Score Matrix:** It is obtained by applying the necessary score functions (from Definition 3.3.2 and Definition 3.3.3) on each entry d_{ij} of matrix D (to discriminate different IVFFNs). Score matrix is denoted by $SC(D) = (S(d_{ij}))_{l\times n_1}$, where $S(d_{ij})$ represents the necessary score function values of each d_{ij}.
4. **Dominance Relation Matrix:**
Dominance relation matrix (DRM) is denoted by R_{DoM} and obtained by using Definition 3.3.3, to decide whether $S(d_{i_1 j}) >_{C_j} S(d_{i_2 j})$ or $S(d_{i_1 j}) =_{C_j} S(d_{i_2 j})$ for all $C_j \in C_{GDM}$ for some fixed i_1, i_2 from $j = 1, 2, \dots, n_1$; $i = 1, 2, \dots, l$.
This step contains the following sub-steps,
(a) Calculate $B_{A_{i_1}}(S(d_{i_1 j}), S(d_{i_2 j}))$ (for some fixed i_1, i_2 from l alternatives) using $B_{A_{i_1}}(S(d_{i_1 j}), S(d_{i_2 j})) = \{C_j \in C_{GDM} | S(d_{i_1 j}) >_{C_j} S(d_{i_2 j})\}$. That is, by using $B_{A_{i_1}}(S(d_{i_1 j}), S(d_{i_2 j}))$, we find the list of criteria under which the alternative A_{i_1} is better (greater) than alternative A_{i_2}. A similar argument is true for all the entries of the score matrix.
(b) Calculate $C_{A_{i_1}}(S(d_{i_1 j}), S(d_{i_2 j}))$ (for some fixed i_1, i_2 from l alternatives) using $C_{A_{i_1}}(S(d_{i_1 j}), S(d_{i_2 j})) = \{C_j \in C_{GDM} | S(d_{i_1 j}) =_{C_j} S(d_{i_2 j})\}$. That is, by using $C_{A_{i_1}}(S(d_{i_1 j}), S(d_{i_2 j}))$, we find the list of criteria under which the alternative A_{i_1} is equal to the alternative A_{i_2}. A similar argument is true for all the entries of the score matrix.
That is, R_{DoM} is an $l \times n_1$ matrix in which each entry consist of two sets namely $B_{A_{i_1}}(S(d_{i_1 j}), S(d_{i_2 j}))$, $C_{A_{i_1}}(S(d_{i_1 j}), S(d_{i_2 j}))$ represent the list of criteria under which the alternative A_{i_1} is better (greater) than alternative A_{i_2} and the alternative A_{i_1} is equal to alternative A_{i_2}, respectively.
Also, $B_{A_{i_1}}(S(d_{i_1 j}), S(d_{i_2 j}))$ and $C_{A_{i_1}}(S(d_{i_1 j}), S(d_{i_2 j}))$ is used to find how one alternative is dominant over the other by using their performance with respect to all the sub-criteria. Note: Here, we can use any other ranking principle for IVFFNs other than Definition 3.3.3. However, we have used Definition 3.3.3 since it defines a total order relation on the class of IVFFNs. The Comparative analysis section will explain the reason for choosing this ranking principle (Definition 3.3.3).
5. **Weighted interval-valued Fermatean fuzzy dominance relation matrix**:
It is an $l \times l$ matrix denoted by $WD = (WD(A_i, A_j))_{l\times l}$ and obtained by using,
$$WD(A_i, A_j) = \sum_{C_j \in B_{A_i}(S(d_{i_1 j}), S(d_{i_2 j}))} K_{C_j} + \frac{\sum_{C_j \in C_{A_i}(S(d_{i_1 j}), S(d_{i_2 j}))} K_{C_j}}{2},$$
for $i, j = 1, 2, \dots, l$ (4.7)

The first summation in the above equation is the sum of weights of all the sub-criteria under which the alternative A_i is better than the other alternatives A_j, for $i \neq j$. Similarly, the second term represents the sum of weights of all the sub-criteria under

Table 1
Set of alternatives.

Alternatives	
A1	Incremental adoption of digital technologies in urban mobility for Reducing Energy Consumption and Greenhouse Gases (GHGs)
A2	Using disruptive digitalization technologies in urban mobility for Reducing Energy Consumption and Greenhouse Gases (GHGs)
A3	Redesign of urban mobility through regulatory approaches and economic instruments

Table 2
Set of main and sub-criteria involved in the case study problem.

Main criteria		Type
Digital Carbon Footprint Awareness Aspect (MC_1)		
C_1	Increased awareness of the personal impact on digital carbon footprint	Benefit
C_2	Lack of involvement, diversity, and inclusion; aligned measurements and goals	Cost
C_3	Enabling greener choices through awareness	Benefit
Environmental and Health Aspect (MC_2)		
C_4	Emission reduction	Benefit
C_5	Improved mental health and wellness	Benefit
Efficiency and Sustainability Aspect (MC_3)		
C_6	Challenges with energy storage and low-carbon fuel energy density	Cost
C_7	Need for accelerating the energy transition	Cost
C_8	Allowing for a better balance between proximity and mobility	Benefit
C_9	Providing sustainable accessibility	Benefit
Management Aspect (MC_4)		
C_{10}	The managing capability of climate transition risks	Benefit
C_{11}	With good data and tools, organizations augment their ability to make faster, more effective decisions	Benefit
C_{12}	An improved organization and management of public space (shared modes, public transport becomes the fastest)	Benefit
C_{13}	Increased need for interoperability, longevity and security	Cost

which the alternative A_i is equal to the other alternatives A_j divided by 2.
Note: Each entry in this matrix represents the dominance of one alternative A_i with respect to the other alternative A_j.

6. **The entire dominance degree:** The entire dominance degree of each object (alternative) $WD(A_i)$ is calculated using the following formula,

$$WD(A_i) = \frac{1}{|U_I|} \sum_{j=1}^{|U_I|} WD(A_i, A_j) \tag{4.8}$$

. Where $|U_I|$ represents the number of sub-criteria.

7. **Ranking of Alternatives:** Finally, the objects (alternatives) are ranked using the entire dominance degree. The larger the value of $WD(A_i)$ better is the object.

5. Case study

Climate change, which has been identified as a growing threat in recent years, is critical for both current and future generations. This issue's escalating severity leads to a loss in freshwater supplies, an increase in arid lands, and an increase in the frequency of forest fires, water crises, and wars, among other repercussions. Reducing or even preventing climate change can be accomplished by enhancing the efficiency of energy use in urban mobility while accounting for the digital carbon footprint. Energy consumption and greenhouse gas emissions are decreased by ensuring energy efficiency. A clean and green future can be reached by creating a sustainable and efficient environment.

A case scenario was developed, which the experts would utilize to respond to the questionnaires. This fictitious city is a densely populated metropolitan area with high traffic density and high greenhouse gas emissions. The case study is about energy use and reducing greenhouse gas emissions. To demonstrate the significance of the research, an imaginary location was created with a dense population, highly traded activities, well-educated people, and intense climatic change. Decision-makers regard energy as a cost-effective and long-term solution to the challenge of climate change. As a result, decision-makers explored three different alternatives. These alternatives frequently involve creative and radical technologies and managerial strategies to rule society. The proposed MCDM tool was utilized to better evaluate these alternatives and identify the optimal choice.

5.1. Proposed methodology results

In this subsection, we use the proposed 'Two-Phase interval-valued Fermatean fuzzy Dominance Method (TPIVFFDM)' to solve a case study problem discussed above. The alternatives, main, and sub-criteria are identified from the literature survey and interviews with Experts. The set of alternatives and main, sub-criteria are given in Table 1 and Table 2, respectively.

We convert the considered case study problem into an IVFFMCGDM problem and solve it using algorithm 4.1. From Tables 1 and 2, we understand that we need to evaluate three alternatives based on their performance with respect to all four main criteria which are further classified into 13 sub-criteria. Our first aim (Phase I) of the algorithm is to find the normalized final weights of all the main and sub-criteria involved in the case study problem. We asked six experts to give their opinion about the relative importance of each main criterion.

Initially, they used a linguistic 9-point scale (linguistic terms are taken from Table 3) to describe the relative importance of all the four main criteria (namely MC_1, MC_2, MC_3, MC_4) and are given in Table 4. Then those linguistic terms are converted into an IVFFN by using Table 3.

By applying step 2 of Phase I, we get the aggregated importance and the final weights W_i of all the main criteria. Table 5 represents

Table 3
IVFFNs equivalent for the linguistic terms.

Linguistic terms	IVFFNs equivalent for the linguistic terms $([a_i, b_i], [c_i, d_i])$ with $b_i^3 + d_i^3 \leq 1$
EL	([0.10,0.20],[0.80,0.95])
VL	([0.20,0.30],[0.75,0.85])
L	([0.30,0.40],[0.70,0.80])
ML	([0.40,0.50],[0.60,0.70])
M	([0.50,0.60],[0.50,0.60])
MH	([0.60,0.70],[0.40,0.50])
H	([0.70,0.80],[0.30,0.40])
VH	([0.75,0.85],[0.20,0.30])
EH	([0.80,0.95],[0.10,0.20])

Note: Extremely Low (EL), Very Low (VL), Low (L), Medium Low (ML), Medium (M), Medium High (MH), High (H), Very High (VH), Extremely High (EH)

Table 4
Expert's opinion about the importance of main criteria.

Main Criteria	Expert 1	Expert 2	Expert 3	Expert 4	Expert 5	Expert 6
MC_1	H	M	VH	VH	VH	VH
MC_2	M	VH	H	MH	EH	H
MC_3	VH	EH	H	AH	H	H
MC_4	H	H	MH	H	L	MH

Table 5
Aggregated Importance and final weights of four main criteria.

Aggregated Importance of Main criteria	$([a_i, b_i], [c_i, d_i])$	J_M score	Final weight (W_i)
MC_1	([0.7,0.8],[0.2667,0.3667])	0.3934	0.293
MC_2	([0.675,0.783],[0.3,0.4])	0.3486	0.259
MC_3	([0.708,0.8167][0.2667,0.3667])	0.4159	0.31
MC_4	([0.6,0.7],[0.4,0.5])	0.185	0.138

Table 6
Expert's opinion about the importance of all thirteen sub-criteria with respect to four main criteria MC_1, MC_2, MC_3, MC_4.

	Expert 1	Expert 2	Expert 3	Expert 4	Expert 5	Expert 6
Digital Carbon Footprint Awareness Aspect (MC_1)						
C_1	VH	EH	H	VH	MH	VH
C_2	H	VH	VH	H	ML	M
C_3	VH	M	MH	EH	VH	MH
Environmental and Health Aspect (MC_2)						
C_4	EH	EH	H	EH	VH	VH
C_5	M	MH	H	H	EH	MH
Efficiency and Sustainability Aspect (MC_3)						
C_6	H	H	MH	H	EL	VH
C_7	VH	ML	MH	E	L	H
C_8	VH	ML	M	EH	M	MH
C_9	EH	VH	MH	VH	M	MH
Management Aspect (MC_4)						
C_6	MH	MH	H	EH	VH	EH
C_7	EH	VH	H	VH	EH	VH
C_8	VH	H	MH	M	ML	M
C_9	H	H	M	MH	M	M

the aggregated importance and final weights of all four main criteria. Similarly, experts gave their opinion about all the thirteen sub-criteria using a 9-point linguistic scale and it is given in Table 6

Using Step 2 of Phase I, we get the aggregated importance and the final weights $W_{i'}$ of all the 13 sub-criteria. Table 7 represents the aggregated importance and final weights of all the thirteen sub-criteria under four main criteria. The normalized final weight K_i of all the thirteen sub-criteria by considering the four main criteria are calculated using Steps 3 and 4 of Phase I and it is given in Table 8. Phase I is complete now. At the end of Phase I, we calculated the normalized weights of all thirteen sub-criteria concerning four main criteria weights. Now we continue to Phase II. In Phase II, firstly the

Table 7
Aggregated Importance and final weights of all thirteen sub-criteria.

Aggregated Importance of sub-criteria	$S_i = ([a_i, b_i], [c_i, d_i])$	$J_M(S_i)$ score	Final weight ($W_{i'}$)
C_1	([0.7250,0.8333],[0.2333,0.3333])	0.4550	0.112
C_2	([0.6333,0.7333],[0.3500,0.4500])	0.2572	0.063
C_3	([0.6667,0.7750],[0.3000,0.4000])	0.3354	0.082
C_4	([0.7667,0.8917],[0.1667,0.2667])	0.5680	0.139
C_5	([0.6500,0.7583],[0.3333,0.4333])	0.2962	0.073
C_6	([0.5917,0.6917],[0.3833,0.4917])	0.1814	0.045
C_7	([0.5917,0.7000],[0.3833,0.4833])	0.1904	0.047
C_8	([0.5917,0.7000],[0.3833,0.4833])	0.1904	0.047
C_9	([0.6667,0.7750],[0.3000,0.4000])	0.3354	0.082
C_{10}	([0.7083,0.8250],[0.2500,0.3500])	0.4292	0.105
C_{11}	([0.7583,0.8750],[0.1833,0.2833])	0.5386	0.132
C_{12}	([0.5750,0.6750],[0.4167,0.5167])	0.1437	0.035
C_{13}	([0.5833,0.6833],[0.4167,0.5167])	0.1537	0.038

Table 8
Normalized final weights of all the thirteen sub-criteria concerning four main criteria final weights.

	Sub-criteria weight ($W_{i'}$)	Main criteria weight (W_i)	Final weight ($W_i'' = W_{i'} * W_i$)	Normalized final weight ($K_i = \frac{W_i''}{\sum_{i=1}^{n_1} W_i''}$)
C_1	0.112	0.293	0.032816	0.136
C_2	0.063	0.293	0.018459 3	0.076
C_3	0.082	0.293	0.024026	0.1
C_4	0.139	0.259	0.036001	0.149
C_5	0.073	0.259	0.018907	0.078
C_6	0.045	0.31	0.01395	0.058
C_7	0.047	0.31	0.01457	0.06
C_8	0.047	0.31	0.01457	0.06
C_9	0.082	0.31	0.02542	0.105
C_{10}	0.105	0.138	0.01449	0.06
C_{11}	0.132	0.138	0.018216	0.076
C_{12}	0.035	0.138	0.00483	0.02
C_{13}	0.038	0.138	0.005244	0.022

Table 9
Performance of Alternatives with respect to thirteen criteria (marked by six experts).

A_i/C_j	Expert 1			Expert 2			Expert 3			Expert 4			Expert 5			Expert 6		
	A_1	A_2	A_3	A_1	A_2	A_3	A_1	A_2	A_3	A_1	A_2	A_3	A_1	A_2	A_3	A_1	A_2	A_3
C_1	H	MH	M	MH	M	VH	H	H	MH	H	EH	MH	VH	M	VH	VH	MH	L
C_2	VL	L	EL	VL	L	ML	MH	H	VH	H	MH	EH	VL	M	M	EH	ML	EH
C_3	VH	H	MH	H	MH	ML	M	ML	MH	ML	M	MH	EH	M	VH	VH	MH	ML
C_4	M	H	EH	VH	H	H	H	H	MH	MH	EH	M	VH	MH	VH	ML	H	EH
C_5	EH	H	VL	EH	MH	ML	VH	MH	M	H	EH	M	EH	VH	EH	EH	M	EL
C_6	H	ML	L	ML	L	VL	EH	M	H	E	EH	VH	ML	VL	L	H	ML	EL
C_7	EH	L	EL	L	VL	VL	MH	H	VH	M	H	EH	ML	VL	EL	VH	L	EL
C_8	MH	H	VH	H	MH	M	ML	L	L	L	ML	L	VL	MH	L	MH	H	VH
C_9	H	VH	EH	VH	H	VH	VH	VH	H	H	EH	MH	MH	H	M	H	H	VH
C_{10}	MH	H	EH	H	MH	MH	VH	H	MH	EH	MH	M	VH	M	ML	H	VH	EH
C_{11}	MH	H	VH	H	M	L	VH	MH	MH	EH	H	MH	EH	MH	VL	MH	H	EH
C_{12}	H	MH	H	VH	M	MH	H	EH	VH	H	VH	MH	M	H	L	MH	H	VH
C_{13}	L	ML	L	M	L	ML	VH	VH	EH	H	EH	VH	M	H	M	H	ML	VL

six experts were asked to give their choices about the three alternatives based on their performance with respect to all the thirteen sub-criteria concerning main criteria and are given in Table 9.

Further, each of these linguistic terms is converted into an IVFFN. By applying Step 2 of Phase II, we get the aggregated performance of all three alternatives with respect to 13 criteria which are given in Table 10.

Then the score matrix is obtained by using Step 3 of Phase II and it is given in Table 11. Even though we consider four score functions for comparing arbitrary IVFFNs, in Table 11 calculations we consider only J_M score, because membership score (J_M) itself is able to differentiate all the IVIFNs present in Table 10.

Now, we get a weighted interval-valued Fermatean fuzzy dominance relation matrix by using Step 4 and Step 5 of Phase II. $WD(A_i, A_j)$ is given in Table 12. The entire dominance degree is obtained by using step 6 of Phase II and it is given in Table 12. The final ranking of alternatives is done based on their entire dominance degree and by using Step 7 of Phase II, we obtain the final ranking as $A_1 > A_2 > A_3$.

5.2. Sensitivity analysis

In this subsection, we discuss the sensitivity analysis based on the results of a case study problem considered earlier. In the case study problem, we have thirteen criteria associated and 4 out of 13

Table 10
Aggregated performance of alternatives A_j with respect to Criteria C_i, for $j = 1, 2, 3, i = 1, 2, \ldots, 13$.

	C_1	C_2	C_3
A_1	([0.7,0.8],[0.283,0.383])	([0.45,0.558],[0.508,0.608])	([0.65,0.758],[0.3167,0.4167])
A_2	([0.6167,0.725],[0.3667,0.4667])	([0.4667,0.5667],[0.53,0.63])	([0.55,0.65],[0.45,0.55])
A_3	([0.583, 0.683],[0.4,0.5])	([0.558,0.675],[0.383,0.4916])	([0.5583,0.6583],[0.43,0.53])
	C_4	C_5	C_6
A_1	([0.6167,0.7167],[0.3667,0.4667])	([0.775,0.908],[0.15,0.25])	([0.6333,0.75],[0.333,0.4333])
A_2	([0.7,0.808],[0.283,0.383])	([0.6583,0.7667],[0.3167,0.4167])	([0.4333,0.5417],[0.5416,0.6417])
A_3	([0.6917,0.808],[0.2667,0.3667])	([0.4167,0.525],[0.5417,0.65])	([0.3917,0.4917],[0.575,0.683])
	C_7	C_8	C_9
A_1	([0.5583,0.6667],[0.4167,0.5167])	([0.4667,0.5667],[0.5250,0.6250])	([0.7000,0.8000],[0.2833,0.3833])
A_2	([0.4000,0.5000],[0.5833,0.6833])	([0.5500,0.6500],[0.4500,0.5500])	([0.7333,0.8417],[0.2333,0.3333])
A_3	([0.3417,0.4500],[0.5750,0.7000])	([0.4833,0.5833],[0.5000,0.6000])	([0.6833,0.7917],[0.2833,0.3833])
	C_{10}	C_{11}	C_{12}
A_1	([0.7167,0.8250],[0.25,0.35])	([0.7083,0.8250],[0.2500,0.3500])	([0.6583,0.7583],[0.3333,0.4333])
A_2	([0.6417,0.7417],[0.35,0.45])	([0.6333,0.7333],[0.3667,0.4667])	([0.6750,0.7833],[0.30,0.40])
A_3	([0.6167,0.7333],[0.35,0.45])	([0.5417,0.6500],[0.4250,0.5250])	([0.6167,0.7167],[0.3667,0.4667])
	C_{13}		
A_1	([0.5750,0.6750],[0.4167,0.5167])		
A_2	([0.5583,0.6667],[0.4167,0.5167])		
A_3	([0.4917,0.6000],[0.4750,0.5750])		

Table 11
J_M score for the aggregated performance of all the three alternatives with respect to thirteen criteria.

J_M score	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}	C_{11}	C_{12}	C_{13}
A_1	0.3880	−0.0457	0.3033	0.2258	0.5980	0.2788	0.1300	−0.0526	0.3880	0.4356	0.4292	0.3015	0.1437
A_2	0.2323	−0.0611	0.0918	0.3960	0.3159	−0.0914	−0.1643	0.0917	0.4704	0.2691	0.2487	0.3486	0.1300
A_3	0.1643	0.1532	0.1132	0.3954	−0.1083	−0.1651	−0.2010	−0.0148	0.3681	0.2474	0.1060	0.2258	0.0188

Table 12
Weighted Fermatean fuzzy dominance relation between alternatives.

$WD(A_i, A_j)$	A_1	A_2	A_3	$WD(A_i), i = 1, 2, \ldots, l$
A_1	0.5	0.666	0.775	0.647
A_2	0.334	0.5	0.824	0.5527
A_3	0.225	0.176	0.5	0.3003

Table 13
Weights of all the 13 criteria by considering 35.2%, 26.8%, 27.8%, 10.2% for cost criteria and 17.3%, 12.7%, 19%, 9.9%, 7.7%, 13.4%, 7.7%, 9.7%, 2.6% for benefit criteria.

$S_t(B,C)/C_i$	S_1(0.784, 0.216)	S_2(0.5,0.5)	S_3(0.6,0.4)	S_4(0.7,0.3)	S_5(0.8,0.2)	S_6(0.9,0.1)	S_7(1,0)	S_8(0.4,0.6)	S_9(0.3,0.7)	S_{10}(0.2,0.8)	S_{11}(0.1,0.9)	S_{12}(0,1)
C_1	0.136	0.0865	0.1038	0.1211	0.1384	0.1557	0.173	0.0692	0.0519	0.0346	0.0173	0
C_2	0.076	0.176	0.1408	0.1056	0.0704	0.0352	0	0.2112	0.2464	0.2816	0.3168	0.352
C_3	0.1	0.0635	0.0762	0.0889	0.1016	0.1143	0.127	0.0508	0.0381	0.0254	0.0127	0
C_4	0.149	0.095	0.114	0.133	0.152	0.171	0.19	0.076	0.057	0.038	0.019	0
C_5	0.078	0.0495	0.0594	0.0693	0.0792	0.0891	0.099	0.0396	0.0297	0.0198	0.0099	0
C_6	0.058	0.134	0.1072	0.0804	0.0536	0.0268	0	0.1608	0.1876	0.2144	0.2412	0.268
C_7	0.06	0.139	0.1112	0.0834	0.0556	0.0278	0	0.1668	0.1946	0.2224	0.2502	0.278
C_8	0.06	0.0385	0.0462	0.0539	0.0616	0.0693	0.077	0.0308	0.0231	0.0154	0.0077	0
C_9	0.105	0.067	0.0804	0.0938	0.1072	0.1206	0.134	0.0536	0.0402	0.0268	0.0134	0
C_{10}	0.06	0.0385	0.0462	0.0539	0.0616	0.0693	0.077	0.0308	0.0231	0.0154	0.0077	0
C_{11}	0.076	0.0485	0.0582	0.0679	0.0776	0.0873	0.097	0.0388	0.0291	0.0194	0.0097	0
C_{12}	0.02	0.013	0.0156	0.0182	0.0208	0.0234	0.026	0.0104	0.0078	0.0052	0.0026	0
C_{13}	0.022	0.051	0.0408	0.0306	0.0204	0.0102	0	0.0612	0.0714	0.0816	0.0918	0.102

are cost criteria, 9 out of 13 are benefit criteria. Our main aim in this subsection is to discuss the results of a case study problem by changing the weights of benefit and cost criteria. Also, from Table 7, we understand the importance of each cost criteria with respect to the cost category is C_2, C_6, C_7, and C_{13} with the following percentage 35.2%, 26.8%, 27.8%, and 10.2%, respectively. Similarly, each benefit criteria $C_1, C_3, C_4, C_5, C_8, C_9, C_{10}, C_{11}$, and C_{12} with the following percentage 17.3%, 12.7%, 19%, 9.9%, 7.7%, 13.4%, 7.7%, 9.7%, and 2.6%, respectively. These percentages are the outcome of the expert's opinion and hence we are going to follow the same percentage for all the calculations in the sensitivity analysis. We know that the sum of the weights of all thirteen criteria must be equal to 1. Now, first, we are going to consider different weights for the Benefit and cost criteria category. Then, we calculate the weights of all the thirteen criteria (by considering the earlier percentage), and it is given in Table 13.

In Table 13, we consider 12 scenarios (S_1 to S_{12}) for calculating weights and see the changes in the results with respect to different criteria weights. $S_t(B, C)$ represents the tth scenario which considers B% for benefit criteria and C% for cost criteria. For example, let us consider the 4-th column in Table 13, it represents the 3-rd scenario

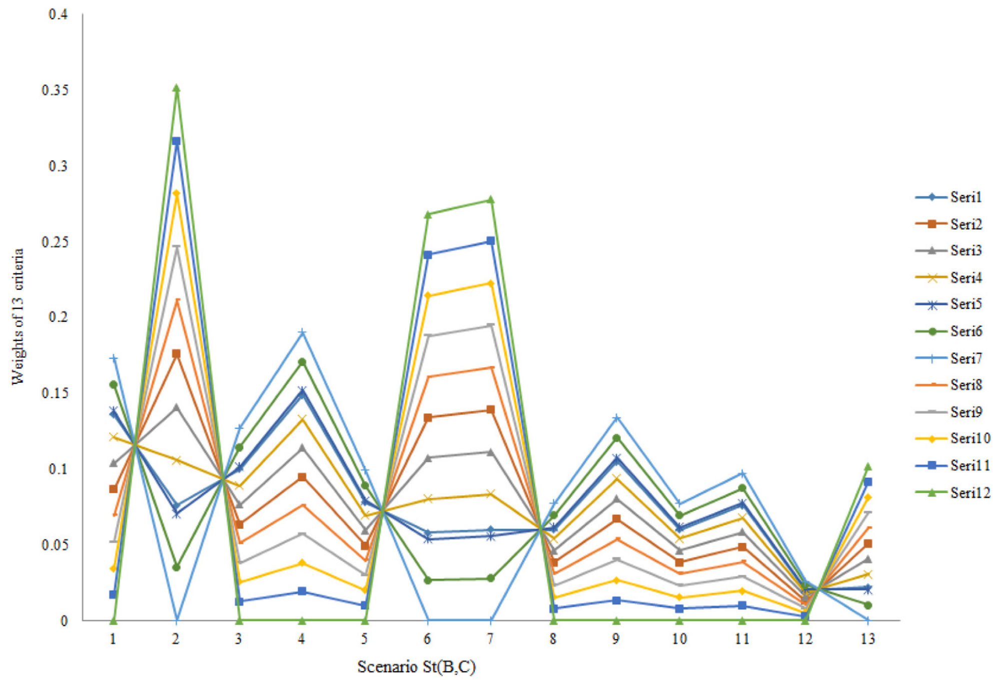

Fig. 1. Distribution of weights with respect to 12 scenario.

Table 14
Ranking of Alternatives for all the 12 scenario.

	$WD(A_1)$	$WD(A_2)$	$WD(A_3)$	Ranking order
S_1	0.647	0.552	0.3	$A_1 > A_2 > A_3$
S_2	0.671	0.491	0.336	$A_1 > A_2 > A_3$
S_3	0.663	0.513	0.324	$A_1 > A_2 > A_3$
S_4	0.654	0.534	0.311	$A_1 > A_2 > A_3$
S_5	0.645	0.556	0.298	$A_1 > A_2 > A_3$
S_6	0.636	0.578	0.285	$A_1 > A_2 > A_3$
S_7	0.627	0.6	0.272	$A_1 > A_2 > A_3$
S_8	0.68	0.469	0.349	$A_1 > A_2 > A_3$
S_9	0.689	0.447	0.362	$A_1 > A_2 > A_3$
S_{10}	0.698	0.426	0.375	$A_1 > A_2 > A_3$
S_{11}	0.707	0.404	0.388	$A_1 > A_2 > A_3$
S_{12}	0.716	0.382	0.401	$A_1 > A_2 > A_3$

which considers 0.6 (60%) weightage for Benefit criteria and 0.4 (40%) weightage for the Cost criteria category. The values in the 4-th column are calculated by multiplying the weightage for benefit criteria (from scenario 3, it is 0.6) and the corresponding percentage of a particular benefit criterion (17.3%, 12.7%, 19%, 9.9%, 7.7%, 13.4%, 7.7%, 9.7%, 2.6%). That is, the value in the 4-th column corresponding to C_5 is calculated by multiplying 0.6 and 0.099 which is equal to 0.0594 (Here, 0.6 comes from 60% and 0.099 comes from 9.9% corresponding to C_5). All other values in the table are calculated in a similar way.

By applying the proposed algorithm (Algorithm 4.1), we get the ranking of alternatives for all the 12 scenarios and it is represented in Table 14. The pictorial representation of how the weights (Table 13) are distributed with respect to the 12 scenarios is shown in Fig. 1. From Table 14, we conclude that all the time Alternative A_1 is considered the best.

5.3. Comparative analysis

In the proposed TPIVFFDM method, we used the total ordering principle on the class of IVFFNs. That is, we are using four score functions to find which alternative is better than the other when we calculate the dominance degree. Researchers can replace this total ranking principle (Definition 3.3.3) with any other simple ranking principle (ranking functions) defined on the class of IVFFNs. In this subsection, we discuss the importance of using a total ordering principle by comparing our proposed method with the recent existing methods, which will show the efficacy of using the total ordering principle in the algorithm. We explain the efficacy by using an illustrative example given below,

Example: Let us consider the general example in which five alternatives A_1, A_2, A_3, A_4, A_5 are there to be evaluated based on five different criteria C_1, C_2, C_3, C_4, C_5. Let us assume the weights of all the five criteria C_1, C_2, C_3, C_4, and C_5 as $0.125, 0.375, 0.095, 0.225$, and 0.180 respectively. For simplicity, We consider only one decision-maker to evaluate the performance of alternatives. Performance of Alternative A_i with respect to criteria C_j is given (in the form of IVFFNs) in Table 15.

Now, by using the proposed two-phase method, we get the Dominance degree matrix and listed in Table 16. Therefore, by using the entire dominance degree ($WD(A_i)$) and step 7 of Phase II (of Algorithm 4.1), we get the ranking order of alternatives as $A_2 > A_1 > A_5 > A_4 > A_3$. i.e., Alternative 2 is considered the best among 5 alternatives.

In the calculations of Table 16, we have used the total ordering principle to check which alternative is better than the other alternative or equal to the other alternative. Rani and Mishra (2022) have proposed the score, and accuracy functions for any IVFFNs and introduced a ranking principle based on them. Suppose if we use Rani and Mishra's ranking principle (Definition A.0.4 instead of total ordering principle

Table 15
Performance of all the 5 alternatives with respect to 5 criteria.

	C_1	C_2	C_3
A_1	$\left(\left[\sqrt[3]{0.22}, \sqrt[3]{0.28}\right], [\sqrt[3]{0.22}, \sqrt[3]{0.28}]\right)$	$([\sqrt[3]{0.1}, \sqrt[3]{0.4}], [\sqrt[3]{0.1}, \sqrt[3]{0.4}])$	$([\sqrt[3]{0.1}, \sqrt[3]{0.5}], [\sqrt[3]{0.1}, \sqrt[3]{0.5}])$
A_2	$([\sqrt[3]{0.25}, \sqrt[3]{0.25}], [\sqrt[3]{0.25}, \sqrt[3]{0.25}])$	$([0, \sqrt[3]{0.5}], [0, \sqrt[3]{0.5}])$	$([\sqrt[3]{0.3}, \sqrt[3]{0.3}], [\sqrt[3]{0.3}, \sqrt[3]{0.3}])$
A_3	$([\sqrt[3]{0.2}, \sqrt[3]{0.3}], [\sqrt[3]{0.2}, \sqrt[3]{0.3}])$	$([\sqrt[3]{0.25}, \sqrt[3]{0.25}], [\sqrt[3]{0.25}, \sqrt[3]{0.25}])$	$([\sqrt[3]{0.23}, \sqrt[3]{0.37}], [\sqrt[3]{0.23}, \sqrt[3]{0.37}])$
A_4	$([\sqrt[3]{0.2}, \sqrt[3]{0.3}], [\sqrt[3]{0.2}, \sqrt[3]{0.3}])$	$([\sqrt[3]{0.13}, \sqrt[3]{0.37}], [\sqrt[3]{0.13}, \sqrt[3]{0.37}])$	$([\sqrt[3]{0.18}, \sqrt[3]{0.42}], [\sqrt[3]{0.18}, \sqrt[3]{0.42}])$
A_5	$([0, \sqrt[3]{0.5}], [0, \sqrt[3]{0.5}])$	$([\sqrt[3]{0.22}, \sqrt[3]{0.28}], [\sqrt[3]{0.22}, \sqrt[3]{0.28}])$	$([\sqrt[3]{0.13}, \sqrt[3]{0.47}], [\sqrt[3]{0.13}, \sqrt[3]{0.47}])$
	C_4	C_5	
A_1	$([\sqrt[3]{0.25}, \sqrt[3]{0.35}], [\sqrt[3]{0.25}, \sqrt[3]{0.35}])$	$([\sqrt[3]{0.1}, \sqrt[3]{0.35}], [\sqrt[3]{0.1}, \sqrt[3]{0.35}])$	
A_2	$([\sqrt[3]{0.1}, \sqrt[3]{0.5}], [\sqrt[3]{0.1}, \sqrt[3]{0.5}])$	$([0, \sqrt[3]{0.45}], [0, \sqrt[3]{0.45}])$	
A_3	$([\sqrt[3]{0.18}, \sqrt[3]{0.42}], [\sqrt[3]{0.18}, \sqrt[3]{0.42}])$	$([\sqrt[3]{0.17}, \sqrt[3]{0.28}], [\sqrt[3]{0.17}, \sqrt[3]{0.28}])$	
A_4	$([\sqrt[3]{0.23}, \sqrt[3]{0.37}], [\sqrt[3]{0.23}, \sqrt[3]{0.37}])$	$([\sqrt[3]{0.22}, \sqrt[3]{0.23}], [\sqrt[3]{0.22}, \sqrt[3]{0.23}])$	
A_5	$([\sqrt[3]{0.23}, \sqrt[3]{0.37}], [\sqrt[3]{0.23}, \sqrt[3]{0.37}])$	$([\sqrt[3]{0.13}, \sqrt[3]{0.32}], [\sqrt[3]{0.13}, \sqrt[3]{0.32}])$	

Table 16
Final results of the example by using Two-Phase method.

	A_1	A_2	A_3	A_4	A_5	$WD(A_i)$
A_1	0.5	0.22	0.65	0.65	0.65	0.534
A_2	0.78	0.5	0.78	0.78	0.78	0.724
A_3	0.35	0.22	0.5	0.4675	0.225	0.3525
A_4	0.35	0.22	0.5325	0.5	0.4875	0.418
A_5	0.35	0.22	0.775	0.5125	0.5	0.4715

Table 17
Final results of Example by using Rani and Mishra's (Rani and Mishra, 2022) and Rani et al.'s (Rani et al., 2022) ranking principle results.

	A_1	A_2	A_3	A_4	A_5	Rani and Mishra $WD(A_i)$	Rani et al. $WD(A_i)$
A_1	0.5	0.5	0.5	0.5	0.5	0.5	0.5
A_2	0.5	0.5	0.5	0.5	0.5	0.5	0.5
A_3	0.5	0.5	0.5	0.5	0.5	0.5	0.5
A_4	0.5	0.5	0.5	0.5	0.5	0.5	0.5
A_5	0.5	0.5	0.5	0.5	0.5	0.5	0.5

Definition 3.3.3) to check which alternative is better than the other alternative or equal to the other alternative and the results ($A_1 = A_2 = A_3 = A_4 = A_5$) are given in Table 17. That is, if we use Rani and Mishra's ranking principle in the calculation, then we get the equal dominance degree for all 5 alternatives (can be seen from Table 17) which implies that all the five alternatives are ranked as equal. However, from Table 15, it is clear that the performance of all the five alternatives is different with respect to different criteria.

In 2022, Rani et al. (2022) proposed a new ranking principle by using 4 score functions defined on the set of IVFFNs. However, this ranking principle (Definition A.0.6) also does not define a total ordering on the set of IVFFNs. Therefore, if we use Rani et al.'s (2022) ranking principle (Definition A.0.6) instead of the total ordering principle, then we get the illogical results which can be seen from Table 17. Rani et al.'s ranking principle also rank all five alternatives as the same (see Table 17) which is illogical.

Therefore, from Table 16, and Table 17, we can conclude that the proposed Two-Phase interval-valued Fermatean fuzzy dominance method is more robust/ reliable when we consider a total ordering principle (Definition 3.3.3) for finding the dominance of one alternative with the remaining alternatives. Also, the changes in the ranking principle change the ranking of alternatives which is the reason why we use the total ordering principle for calculations.

Note: All the entries in Table 17 refer that all the alternatives are equally preferred. But it is clear (from Table 15) that all the alternatives perform differently with respect to different criteria.

6. Results and discussion

For this study, three different alternatives were identified based on the adoption of energy consumption and greenhouse gas reduction. These alternatives were analysed using 13 different criteria grouped into four main aspects. These are digital carbon footprint awareness, environmental and health, efficiency and sustainability, and management. Experts in energy efficiency and digital carbon footprint were engaged to help prioritize the alternatives sustainably and effectively. Questionnaires with 13 different criteria were created for each alternative. The most advantageous alternative was chosen as the incremental use of digital technology in urban mobility.

Apart from the other two alternatives, the incremental use of digital technologies in urban mobility was deemed to be the most advantageous. To maintain energy efficiency, it is critical to gradually implement digital technologies based on urban mobility. While growing slowly, society may adapt to these technologies more swiftly and easily. The steps to combat climate change must provide more concrete outcomes, both promptly and effectively. As a result, considering its sustainability and efficiency in the choice of this alternative, it is judged as the most advantageous.

The second most advantageous alternative was considered to be the use of disruptive digitalization technologies in urban mobility. In some cases, it may be harder to make big changes in how much energy is used and how much greenhouse gases are released. For example, integrating a fully new system rather than upgrading the present public transportation system may not be well received by society. Furthermore, because the system to be integrated may result in a whole new system and additional expenditures, it may not contribute to the desired degree of energy efficiency. Increasing energy efficiency and optimizing the current system may be less expensive than installing a new system. Given the financial, social, and political dangers associated with this alternative, it was deemed unfavourable. However, in rare circumstances, a total system overhaul is unavoidable. No matter how well-optimized the current system is, it may not produce the best results. As a result, the system must be modified, and this predicament highlights the significance of the alternative.

The least advantageous alternative was to redesign urban mobility through regulatory techniques and economic instruments. For example, customers may involuntarily switch to public transportation due to factors such as increased vehicle taxes and lower public transportation rates. Although this circumstance helps to reduce the carbon impact, the fact that it can jeopardize people's comfort and freedom has made it the least acceptable option. Furthermore, regulating urban movement by economic methods may appeal to a specific demographic. For example, tax breaks on the purchase of electric vehicles benefit those who can afford to buy one. However, because persons with limited financial resources will be unable to purchase these automobiles, the tax cut will not affect them.

7. Managerial and policy implications

Energy usage and greenhouse gas reductions are frequently attributed to technological advancements. The decision-makers are to decide whether to employ these technological breakthroughs. Each new technology incurs a cost in terms of implementation. If decision-makers find this technology's use valuable, they incorporate it into their systems. Furthermore, it may be less expensive and more environmentally good to improve and update the old system with new technology rather than fully replace it. The gradual acceptance of digital technology in urban transportation alternatives results in the construction of a sustainable and efficient system, and policymakers base their decisions on the implications of this alternative. Migration caused by wars in the twenty-first century may be similar to migration caused by a climatic crisis. People are anticipated to abandon barren lands and relocate to areas near freshwater sources. Alternatives in research must be considered to delay or prevent these migrations. As a result, policymakers and managers should design future policies to achieve these objectives. However, it will not be sufficient for only wealthy nations to take action in this regard. Developing and underdeveloped countries must participate in the global fight against energy consumption and greenhouse gas emissions by giving economic assistance.

8. Conclusion

In this study, energy consumption and greenhouse gas emissions are evaluated in terms of digital carbon footprint awareness, environmental and health, efficiency and sustainability, and management issues. The findings show that incremental adoption of digital technologies in urban mobility is the most advantageous alternative while redesigning urban mobility through regulatory measures and economic instruments is the least advantageous.

One of the most significant contributions of this research to the literature is the evaluation of alternatives based on novel technological solutions in urban mobility while accounting for the digital carbon footprint. The results serve as a model for governments that are projected to be affected by climate change now and in the future. The alternatives selected in this study were based on the criteria established in the case study, therefore their applicability in other places is uncertain. In addition, the research may be able to address the demands of a greater variety of locations, as the rise in the number of experts will result in a greater diversity of perspectives.

Alternatives and criteria can be varied in future studies. Although we have not yet seen the full extent of the effects of climate change, this issue may have far-reaching negative ramifications in the future. As a result, alternatives can be recreated based on the circumstances of the day. The pilot findings may provide a comprehensive perspective on reducing energy use and greenhouse gas emissions. Changes in the ranking principle change the ranking of alternatives which has been discussed thoroughly in the previous section. This gives a pathway for further research, and one can think of introducing a new ranking principle that can suit the specific problem. However, researchers must try to introduce a new total ordering principle on the set of IVFFNs. Similarly, in the calculations of Phase I and Phase II of the proposed algorithm, researchers may use their own aggregation operators and study the changes in the results based on the aggregation operators. A comparative study can be done by comparing the Two-Phase interval-valued Fermatean fuzzy dominance method with the other alternative methods for solving multi-criteria group decision-making problems. Problems modelled using other types of intuitionistic fuzzy numbers cannot be solved using TPIVFFDM. IVFFNs are better at modelling problems involving incomplete and imprecise information. However, it is not necessary to use IVFFNs (or any other intuitionistic fuzzy number) for all kinds of problems. Certain real-life problems might involve precise data, and during this case, one can go for decision-making algorithms available for real number data. If we use IVFFNs (TPIVFFDM method) for modelling a problem involving real number (precise information) data, then we cannot expect better results which is due to the wrong choice of a fuzzy number. Also, the proposed two-phase method is available for solving problems modelled under the IVFF environment. Researchers can extend the two-phase methodology to other classes of fuzzy and intuitionistic fuzzy numbers. In future, we extend the proposed two-phase method to the class of trapezoidal-valued intuitionistic fuzzy numbers and explore the two-phase ideology by applying it to the problem from other domains.

CRediT authorship contribution statement

Jeevaraj S.: Methodology, Software, Validation, Formal analysis, Writing – original draft, Writing – review & editing, Visualization. **Ilgin Gokasar:** Conceptualization, Data curation, Validation, Formal analysis, Investigation, Writing – original draft, Writing – review & editing, Visualization. **Muhammet Deveci:** Methodology, Software, Validation, Formal analysis, Writing – original draft, Writing – review & editing , Visualization. **Dursun Delen:** Supervision, Validation, Writing – review & editing. **Bilal Bahaa Zaidan:** Supervision, Writing – review & editing. **Xin Wen:** Validation, Writing – review & editing. **Wen-Long Shang:** Validation, Writing – review & editing. **Gang Kou:** Supervision, Writing – review & editing.

Declaration of competing 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.

Data availability

The data that has been used is confidential.

Appendix

Definition A.0.1 (Senapati and Yager, 2019)**.** Let us consider the non-empty universe of discourse X_F. Then a Fermatean fuzzy set which is denoted as $\boldsymbol{F}$ and defined in X_F the form of a 3-tuple as follows, $\boldsymbol{F} = \left\{\langle x, \mu_F(x), \nu_F(x)\rangle : x \in X\right\}$ where $\mu_F : X \to [0,1], \nu_F : X \to [0,1]$ with $0 < (\mu_F(x))^3 + (\nu_F(x))^3 \leq 1$, $\forall x \in X_F$. Also $\mu_F(x)$ represents the membership function of $\boldsymbol{F}$ and $\nu_F(x)$ denotes non-membership function of $\boldsymbol{F}$. The degree of hesitancy for any Fermatean fuzzy set $\boldsymbol{F}$ is denoted by $\pi_F(x)$, and defined as $\pi_F(x) = \sqrt{1 - (\mu_F(x))^3 + (\nu_F(x))^3}$.

Definition A.0.2 (Senapati and Yager, 2019)**.** Let $F = (\mu_F, \nu_F)$ be a FFS. Then the score and accuracy function ($acc(F)$) of F are defined as,

$$score(F) = \mu_F^3 - \nu_F^3, acc(F) = \mu_F^3 + \nu_F^3 \tag{A.1}$$

.

Definition A.0.3 (Senapati and Yager, 2019). Let $F_1 = (\mu_{F_1}, \nu_{F_1})$ and $F_2 = (\mu_{F_2}, \nu_{F_2})$ be any two FFSs. Then the ranking principle using the score and accuracy function is defined as follows,

1. If $score(F_1) < score(F_2)$, then $F_1 < F_2$
2. If $score(F_1) > score(F_2)$, then $F_1 > F_2$
3. If $score(F_1) = score(F_2)$, then
   - If $acc(F_1) < acc(F_2)$, then $F_1 < F_2$
   - If $acc(F_1) > acc(F_2)$, then $F_1 > F_2$
   - If $acc(F_1) = acc(F_2)$, then $F_1 = F_2$.

Definition A.0.4 (Rani and Mishra, 2022). Let $F_I = \langle [f_1, f_2], [f_3, f_4] \rangle$ an IVFFN. Then the score function J_1 of F_I is defined as

$$J_1(F_I) = \frac{{f_1}^3 + {f_2}^3 - {f_3}^3 - {f_4}^3}{2} \tag{A.2}$$

similarly the accuracy function p of F_I is defined as

$$p(F_I) = \frac{{f_1}^3 + {f_2}^3 + {f_3}^3 + {f_4}^3}{2} \tag{A.3}$$

and the ranking principle for comparing any two IVFFNs F_1, F_2 is defined as follows,

- If $J_1(F_1) < J_1(F_2)$ then $F_1 < F_2$
- If $J_1(F_1) > J_1(F_2)$ then $F_1 > F_2$
- If $J(F_1) = J(F_2)$ then
  - If $p(F_1) < p(F_2)$ then $F_1 < F_2$
  - If $p(F_1) > p(F_2)$ then $F_1 > F_2$
  - If $p(F_1) = p(F_2)$ then $F_1 = F_2$.

Definition A.0.5 (Rani et al., 2022). Let $F_1 = \left\langle [\mu_{F_{1L}}, \mu_{F_{1U}}], [\nu_{F_{1L}}, \nu_{F_{1U}}] \right\rangle \in IVFFN$. Then the modified score function J of F_1 is defined as

$$J(F_1) = \frac{(\mu^3_{F_{1L}} - \nu^3_{F_{1L}})(1 + \sqrt[3]{(\mu^3_{F_{1L}} - \nu^3_{F_{1L}})}) + (\mu^3_{F_{1U}} - \nu^3_{F_{1U}})(1 + \sqrt[3]{(\mu^3_{F_{1U}} - \nu^3_{F_{1U}})})}{2} \tag{A.4}$$

Definition A.0.6 (Rani et al., 2022). Let $F_1 = ([\mu_{F_{1L}}, \mu_{F_{1U}}], [\nu_{F_{1L}}, \nu_{F_{1U}}])$, $F_2 = ([\mu_{F_{2L}}, \mu_{F_{2U}}], [\nu_{F_{2L}}, \nu_{F_{2U}}]) \in IVFFN$. Let $J_1(F_i), p(F_i), J_P(F_i)$ and $J(F_i)$ be four score functions (as defined above) for any two IVFFNs (F_1, F_2). Then the ranking principle for comparing any two IVFFNs is defined as follows,

- If $J_1(F_1) < J_1(F_2)$ then $F_1 < F_2$
- If $J_1(F_1) > J_1(F_2)$ then $F_1 > F_2$
- If $J_1(F_1) = J_1(F_2)$ then
  - If $p(F_1) < p(F_2)$ then $F_1 < F_2$
  - If $p(F_1) > p(F_2)$ then $F_1 > F_2$
  - If $p(F_1) = p(F_2)$ then
    - If $J_P(F_1) > J_P(F_2)$ then $F_1 < F_2$
    - If $J_P(F_1) < J_P(F_2)$ then $F_1 > F_2$
    - If $J_P(F_1) = J_P(F_2)$ then
      - If $J(F_1) < J(F_2)$ then $F_1 < F_2$
      - If $J(F_1) > J(F_2)$ then $F_1 > F_2$
      - If $J(F_1) = J(F_2)$ then $F_1 = F_2$

References

Abduljabbar, R.L., Liyanage, S., Dia, H., 2021. The role of micro-mobility in shaping sustainable cities: A systematic literature review. Transp. Res. part D: Transp. Environ. 92, 102734.

Aftab, U., Siddiqui, G.F., 2018. Big data augmentation with data warehouse: A survey. In: 2018 IEEE International Conference on Big Data (Big Data). IEEE, pp. 2785–2794.

Akram, M., Ullah, I., Allahviranloo, T., Edalatpanah, S., 2021. Fully pythagorean fuzzy linear programming problems with equality constraints. Computat. appl. math. 40 (4), 120.

Ali, A., Ullah, K., Hussain, A., 2023. An approach to multi-attribute decision-making based on intuitionistic fuzzy soft information and Aczel-Alsina operational laws. J. Decis. Anal. Intell. Comput. 3 (1), 80–89.

Alrasheedi, M.A., Jeevaraj, S., 2023. Membership score of an interval-valued Pythagorean fuzzy numbers and its applications. IEEE Access.

Berkeley, N., Bailey, D., Jones, A., Jarvis, D., 2017. Assessing the transition towards battery electric vehicles: A multi-level perspective on drivers of, and barriers to, take up. Transp. Res. part A: policy pract. 106, 320–332.

Bouraima, M.B., Qiu, Y., Stević, Željko., Marinković, D., Deveci, M., 2023. Integrated intelligent decision support model for ranking regional transport infrastructure programmes based on performance assessment. Expert Syst. Appl. 222, 119852.

Broumi, S., Mohanaselvi, S., Witczak, T., Talea, M., Bakali, A., Smarandache, F., 2023. Complex fermatean neutrosophic graph and application to decision making. Decis. Mak.: Appl. Manag. Eng. 6 (1), 474–501.

Broumi, S., Sundareswaran, R., Shanmugapriya, M., Nordo, G., Talea, M., Bakali, A., Smarandache, F., 2022. Interval-valued fermatean neutrosophic graphs. In: Collected Papers. Volume XIII: On various scientific topics. Infinite Study, p. 496.

Curtis, C., 2008. Planning for sustainable accessibility: The implementation challenge. Transp. policy 15 (2), 104–112.

Dadashpoor, H., Rostami, F., 2017. Measuring spatial proportionality between service availability, accessibility and mobility: Empirical evidence using spatial equity approach in Iran. J. Transp. Geogr. 65, 44–55.

De La Peña, L., Guo, R., Cao, X., Ni, X., Zhang, W., 2022. Accelerating the energy transition to achieve carbon neutrality. Resour. Conserv. Recy. 177, 105957.

Dia, H., Bagloee, S., Ghaderi, H., 2020. Technology-led disruptions and innovations: The trends transforming urban mobility. Handb. smart cities 1–36.

Dodds, P.E., Garvey, S.D., 2016. The role of energy storage in low-carbon energy systems. In: Storing Energy. Elsevier, pp. 3–22.

EC, 2016. Transport emissions. https://ec.europa.eu/clima/eu-action/transport-emissions_en (Online; Accessed 09 November 2022).

Edstrand, E., 2016. Making the invisible visible: How students make use of carbon footprint calculator in environmental education. Learn. Media Technol. 41 (2), 416–436.

Ejegwa, P., Zuakwagh, D., 2022. Fermatean fuzzy modified composite relation and its application in pattern recognition. J. Fuzzy Extens. Appl. 3 (2), 140–151. http://dx.doi.org/10.22105/jfea.2022.335251.1210.

EPA, 2022. Sources of greenhouse gas emissions. https://www.epa.gov/ghgemissions/sources-greenhouse-gas-emissions#:%7E:text=Transportation%20(27%25%20of%202020%20greenhouse,ships%2C%20trains%2C%20and%20planes (Online; Accessed 09 November 2022).

Falkner, R., 2016. The Paris agreement and the new logic of international climate politics. Int. Aff. 92 (5), 1107–1125.

Fan, Z., Harper, C.D., 2022. Congestion and environmental impacts of short car trip replacement with micromobility modes. Transp. Res. Part D: Transp. Environ. 103, 103173.

Granjal, J., Monteiro, E., Silva, J.S., 2013. End-to-end transport-layer security for internet-integrated sensing applications with mutual and delegated ECC public-key authentication. In: 2013 IFIP Networking Conference. IEEE, pp. 1–9.

Güneri, B., Deveci, M., 2023. Evaluation of supplier selection in the defense industry using q-rung orthopair fuzzy set based EDAS approach. Expert Syst. Appl. 222, 119846.

Hammar, H., Lofgren, A., Sterner, T., 2004. Political economy obstacles to fuel taxation. Energy J. 25 (3).

Hitge, G., Van Dijk, E., 2012. Incremental approach to public transport system improvements. SATC 2012.

Jeevaraj, S., 2021. Ordering of interval-valued fermatean fuzzy sets and its applications. Expert Syst. Appl. 185, 115613.

Jeevaraj, S., 2022. A note on multi-criteria decision-making using a complete ranking of generalized trapezoidal fuzzy numbers. Soft Comput. 26 (21), 11225–11230.

Jeevaraj, S., Rajesh, R., Lakshmana Gomathi Nayagam, V., 2023. A complete ranking of trapezoidal-valued intuitionistic fuzzy number: An application in evaluating social sustainability. Neural Comput. Appl. 35 (8), 5939–5962.

Liu, Y., Cirillo, C., 2015. Model system to evaluate impacts of vehicle purchase tax and fuel tax on household greenhouse gas emissions. Transp. Res. Rec. 2503 (1), 51–59.

Luthra, S., Mangla, S.K., Xu, L., Diabat, A., 2016. Using AHP to evaluate barriers in adopting sustainable consumption and production initiatives in a supply chain. Int. J. Prod. Econ. 181, 342–349.

Majumdar, A., Jeevaraj, S., Kaliyan, M., Agrawal, R., 2021. Selection of resilient suppliers in manufacturing industries post-COVID-19: Implications for economic and social sustainability in emerging economies. Int. J. Emerg. Mark. (ahead-of-print).

May, A.D., Kelly, C., Shepherd, S., 2006. The principles of integration in urban transport strategies. Transp. policy 13 (4), 319–327.

McQueen, M., Abou-Zeid, G., MacArthur, J., Clifton, K., 2021. Transportation transformation: Is micromobility making a macro impact on sustainability? J. Plan. Literat. 36 (1), 46–61.

Mishra, V.N., Kumar, T., Sharma, M.K., Rathour, L., 2023. Pythagorean and fermatean fuzzy sub-group redefined in context of T norm and s conorm. J. Fuzzy Extens. Appl..

Narang, M., Kumar, A., Dhawan, R., 2023. A fuzzy extension of MEREC method using parabolic measure and its applications. J. Decis. Anal. Intell. Comput. 3 (1), 33–46.

Nayagam, V., Jeevaraj, S., Ponnialagan, D., 2017. An intuitionistic fuzzy multi-criteria decision-making method based on non-hesitance score for interval-valued intuitionistic fuzzy sets. Soft. Comput. 21, 7077–7082.

Önden, İ., Deveci, M., Önden, A., 2023. Green energy source storage location analysis based on GIS and fuzzy Einstein based ordinal priority approach. Sustain. Energy Technol. Assess. 57, 103205.

Othman, B., De Nunzio, G., Di Domenico, D., Canudas-de Wit, C., 2019. Ecological traffic management: A review of the modeling and control strategies for improving environmental sustainability of road transportation. Annu. Rev. Control 48, 292–311.

Palanikumar, M., Kausar, N., Ahmed, S.F., Edalatpanah, S.A., Ozbilge, E., Bulut, A., 2023. New applications of various distance techniques to multi-criteria decision-making challenges for ranking Vague sets. AIMS Math. 8 (5), 11397–11424.

Pamucar, D., Deveci, M., Gokasar, I., Tavana, M., Köppen, M., 2022. A metaverse assessment model for sustainable transportation using ordinal priority approach and Aczel-Alsina norms. Technol. Forecast. Soc. Change 182, 121778.

Pamučar, D., Puška, A., Simić, V., Stojanović, I., Deveci, M., 2023. Selection of healthcare waste management treatment using fuzzy rough numbers and Aczel–Alsina function. Eng. Appl. Artif. Intell. 121, 106025.

Pelling, M., 2010. Adaptation to Climate Change: From Resilience to Transformation. Routledge.

Poudenx, P., 2008. The effect of transportation policies on energy consumption and greenhouse gas emission from urban passenger transportation. Transp. Res. Part A: Policy Pract. 42 (6), 901–909.

Rani, P., Mishra, A.R., 2022. Interval-valued fermatean fuzzy sets with multi-criteria weighted aggregated sum product assessment-based decision analysis framework. Neural Comput. Appl. 34, 8051–8067.

Rani, P., Mishra, A.R., Deveci, M., Antucheviciene, J., 2022. New complex proportional assessment approach using Einstein aggregation operators and improved score function for interval-valued fermatean fuzzy sets. Comput. Ind. Eng. 169, 108165.

Rasoulzadeh, M., Edalatpanah, S.A., Fallah, M., Najafi, S.E., 2022. A multi-objective approach based on Markowitz and DEA cross-efficiency models for the intuitionistic fuzzy portfolio selection problem. Decis. Mak.: Appl. Manag. Eng. 5 (2), 241–259.

Sedlmeir, J., Buhl, H.U., Fridgen, G., Keller, R., 2020. The energy consumption of blockchain technology: Beyond myth. Bus. Inform. Syst. Eng. 62 (6), 599–608.

Seligman, C., Darley, J.M., Becker, L.J., 1978. Behavioral approaches to residential energy conservation. Energy build. 1 (3), 325–337.

Selvaraj, J., Gatiyala, P., Hashemkhani Zolfani, S., 2022. Trapezoidal intuitionistic fuzzy power Heronian aggregation operator and its applications to multiple-attribute group decision-making. Axioms 11 (11), 588.

Selvaraj, J., Majumdar, A., 2021. A new ranking method for interval-valued intuitionistic fuzzy numbers and its application in multi-criteria decision-making. Mathematics 9 (21), 2647.

Senapati, T., Yager, R., 2019. Fermatean fuzzy sets. J. Ambient Intell. Hum. Comput. 11, 663–674.

Shaheen, S.A., Lipman, T.E., 2007. Reducing greenhouse emissions and fuel consumption: Sustainable approaches for surface transportation. IATSS Res. 31 (1), 6–20.

Shahid, S., Minhans, A., Puan, O.C., 2014. Assessment of greenhouse gas emission reduction measures in transportation sector of Malaysia. Jurnal teknologi 70 (4).

Spickermann, A., Grienitz, V., Heiko, A., 2014. Heading towards a multimodal city of the future?: Multi-stakeholder scenarios for urban mobility. Technol. Forecast. Soc. Change 89, 201–221.