Fuzzy Einstein WASPAS Approach for the Economic and Societal Dynamics of the Climate Change Mitigation Strategies in Urban Mobility Planning

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Abstract

The recent drastic natural degradation and climate change urge the authorities to transform their traditional policies to take climate action in urban mobility planning. However, the interests of the stakeholders may differ so that the development and the implementation of the required action become challenging. In this study, we trace how an optimal action plan should take the societal dynamics into account and how the taken actions can reshape the societal dynamics. To illustrate and analyze the complex forces that drive the decision-making process in urban mobility planning, we develop a case scenario in which bunches three small-scale urban mobility planning alternatives that are highly proposed in the literature and practiced in cities. Alternatives are assessed under twelve criteria reflecting economic, environmental, technical, and political dimensions of the decision problem. In solving the problem, we propose an improvement of the Weighted Aggregated Sum Product Assessment (WASPAS) approach by applying Einstein norms in a fuzzy environment over triangular fuzzy numbers to evaluate and rank the prioritization of climate change mitigation strategies. The proposed method comprises two stages. In the first stage, the weight coefficients of the criteria are calculated. In the second stage, the fuzzy Einstein WASPAS approach is applied to select the most suitable alternative among the three alternatives. Testing and validation of the model are done through a comparison with existing decision making methods in the literature. The results show that the best plan should be inclusive and equitable as well as economically efficient. Although the economic dimension is highly important in the decision-making process. Choosing the most suitable urban mobility planning option requires the consideration of other societal dynamics, too.

Keywords: Economic dynamics, Climate change, Fuzzy Einstein operators, Multi-criteria decision making, WASPAS.

1. Introduction

Climate change affects and reshapes everything from economics to politics so that it is assumed to be a threat multiplier that is responsible for accelerating other societal problems such as health issues, immigration, food, water or energy insecurity, housing crises, transportation issues. Most of these problems create structural changes. Adaptation to the new order is challenging and requires costly efforts. The complexity of the effects of climate change urges governments, institutions, the business world, and individuals to take strategic actions which are sometimes in conflict.

Despite these conflicts of interests, cooperation is the only way of achieving successful outcomes in taking climate actions especially in sectors like transportation. Achieving a cooperative action in designing public policy is never easy but can be implemented (Elliott and Schlaepfer, 2001). In November 2021, the Glasgow Climate Pact1 adopted at the UN Climate Change Conference (COP26) brought almost 200 countries together to use major international instruments by recognizing the importance of science for effective climate action and policymaking. In this regard, cities that have been densely populated since the beginning of industrialization are now tested by new challenges. While creating livable, environment-friendly, sustainable cities is the new major objective of city governance, the most important constraint now is climate change mitigation. The United States Environmental Protection Agency (EPA) and the European Environment Agency (EEA) report that transportation constitutes almost a quarter of total greenhouse gas emissions (GHG) in Europe, over one-third in the US, and around a quarter in the world. In October 2021, government leaders, industry experts, and civil society groups met

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[1] https://unfccc.int/sites/default/files/resource/cma3_auv_2_cover%2520decision.pdf

in the UN Sustainable Transport Conference in Beijing, China to promise a sustainable future for the transportation sector by taking effective climate action. Decarbonizing all means of transport by cooperative actions of all stakeholders, and creating safe transport for all were emphasized as the major goals. Most significantly, it was stated that public transportation should be the foundation of urban mobility[2].

Unfortunately, urban mobility planning has a lot of other constraints beyond the national commitments that are given for climate actions. Many factors are determining the pace of green transformation in the city. As the report by Intergovernmental Panel on Climate Change (Sims et al., 2014) explains social and cultural factors such as the lack of will, and short-term interested political choices, economic factors such as tax practices for energy resources, restricted financial resources, lack of specialized human capital, political factors such as municipal governments' weak autonomy, low prioritization of urban mobility in budget planning and some technical factors such as missing data or the slow pace of technology diffusion.

Our study focuses on the change of the resource allocation in the society as the climate actions are urged more and more dramatically in urban mobility. The planners are supposed to act taking differing demands of the society regarding different aspects such as financial, social, economic, and so on. Neither the planning nor implementing the necessary action is easy because it requires the consent of different stakeholders in a big transformation from traditional to sustainable. Here, we explore the importance of forces that drive the decision-making process in urban mobility planning. The dynamic relationships between public policies, urban mobility planning, and climate change mitigation strategies are shaped differently under different conditions. Although the IPCC's recent "code red" alarm regarding human-induced climate change has changed the rules of the game, still the optimal choice on the set of alternatives in taking the climate action is subject to a certain set of criteria. The set of criteria that limits the urban mobility plan chosen by the regulatory authority reflects the social, cultural, technical, political, and economic dynamics of the society.

In 2012, European Commission (EC) launched the Sustainability of Urban Mobility Plan (SUMP) as the gas emissions from urban transport increased to unignorable levels in Europe (EC, 2013). Since then, being compatible with climate actions, the EC keeps track of sustainability

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[2] https://www.un.org/en/desa/sustainable-transport-key-green-energy-shift-un-secretary-general

actions and continuously calls all the stakeholders for developing and implementing a sustainable urban mobility plan focusing on people's needs. EC guidelines aim to reshape and transform the traditional approaches in urban mobility planning. However, in 2014, Arsenio et al. (2004) analyzed forty case studies conducted in Europe. Results show that such a paradigm shift is not an easy one.

1.1. The objectives of this study

As we review in the next section, literature exists on both theoretical and empirical studies on the subject. The existing structural changes that are enforced by the climate strategies taken by the regulators are examined from different perspectives. Yet, just a few studies analyze the two-way cause-and-effect relationship between the economic and societal dynamics and the planned climate actions. On the one hand, the necessary strategic transformation of the plans causes a redistribution of the economic and social resources. On the other hand, the demands based upon the economic and societal needs of the public shapes the planners' design of the projects. This study aims to explore the economic and social dimensions of this two-way relationship. As given in the next chapter, the studies in the literature put forward different projects practiced as examples of empirical problems. All these alternatives raise the importance given to the different dimensions of the projects. Collecting different alternatives that supply different needs of the society in a pool and analyzing the effects of economic and other societal factors on the planners' choice gives the opportunity to understand the dynamics of the problem. As we explain in the third chapter, we pool three alternatives that are practiced and offered theoretically on paper in a case scenario. Therefore, we can illustrate the complexity of the decision-making process in urban mobility planning and analyze the role of economic and societal dynamics on the best choice of the planner in the case scenario. We use the findings of the case to explore the structural changes created by the policy shifts and also the dynamic factors that create the policy shifts.

Here, the best option among different projects that use climate change mitigation strategies in urban mobility planning is determined. The experts from academia and the sector are interviewed, and the literature is reviewed in detail in constructing the set of criteria and the set of alternative projects. We take into consideration that the interested groups' preferences for mobility plans may conflict and they may resist implementing the project. Thus, we paid special attention to that the societal dynamics in economic, political, environmental, and technical dimensions are reflected in the set of criteria and the alternatives. Because the literature review reveals higher benefits from the small-scale urban and regional urban mobility projects, the alternatives were chosen among the most possible practices of climate action-driven plans in urban mobility. Therefore, the decision-making process is tested for the three alternatives under twelve criteria with the proposed improvement of the Weighted Aggregated Sum Product Assessment (WASPAS) approach by applying Einstein norms in a fuzzy environment over triangular fuzzy numbers

In this study, we consider the "red-code alarm" on climate change that we are given. The regulatory authorities are urged to take climate action. Urban mobility planning is not an exception. The recent urgent plans are expected to be economically efficient, of course. However, the implementation process requires the collective action of the society. The conflicting interests of the stakeholders may limit the feasibility of the action plan. In that respect, we propose a case in which three small-scale urban mobility planning alternatives are assessed under various societal dynamics. The proposed case is solved by an improved WASPAS model under fuzzy Einstein in a way that the dynamic environment of the decision-making process is considered. The strong stability and robustness of the model allow us to interpret the results safely. The study contributes to the literature by emphasizing and illustrating the two-way causality between economic and societal needs of the society and the climate actions taken by the planners in urban mobility. The case we develop puts forward that among different alternatives, the one care for society's needs can be prior to most economically efficient or most green and sustainable one.

1.2. The motivation of the proposed model

The most commonly used operators in fuzzy theory and decision support systems are the min(imum) and the max(imum) operators (Wu et al., 2018). They are easy to calculate and can be extended into a lattice structure. However, besides the above advantages, their main disadvantage is that the result is determined only by one variable, and the other has no influence. In addition to this shortcoming, Dombi (2009) points out that the min-max operators are not analytical, and their second derivative is not continuous. These shortcomings of the traditional min-max operator in fuzzy theory can be successfully eliminated by using the Einstein operator.

By applying the Einstein operator in a fuzzy environment, the fusion and information processing process are more flexible than the traditional min-max operator. However, one shortcoming of the Einstein norm is the impossibility of fusing information that is represented by values outside the interval [0,1]. This characteristic of Einstein norms limits their application in the field of decision making since, in such systems, attributes are represented by different units of measurement whose range is out of range [0,1]. Hence, processing such information in multi-criteria models using traditional Einstein norms is impossible. To eliminate this limitation of Einstein norms, the improvement of arithmetic operations with Einstein norms in a fuzzy environment is performed in this study. The arithmetic operations with Einstein norms presented in this paper enable the fusion of fuzzy numbers regardless of the interval to which they belong.

In addition to the previously mentioned advantages of the multi-criteria methodology presented in this paper, the following section offers other benefits, which include: *(i)* The fuzzy Einstein WASPAS model enables processing of group information and processing of uncertainties in expert preferences; *(ii)* The proposed multi-criteria decision making (MCDM) model is based on the application of Einstein standards and improves the performance of traditional WASPAS (Zavadskas et al, 2012); *(iii)* In the WASPAS model, Einstein norms were used to transform linear weighted sum and weighted product functions into nonlinear functions; *(iv)* Traditional weighted sum and product functions have been transformed into fuzzy Einstein weighted averaging and fuzzy Einstein weighted geometric averaging functions that enable nonlinear information processing in Einstein WASPAS. In addition, these functions increase the model's flexibility when making decisions in a dynamic environment.

The rest of the paper is as follows: In section 2, the literature is reviewed. Section 3 defines the case and the decision-making problem. The proposed methodology and the improved model to solve the problem are explained in Section 4. The results of the model and the solutions to the case problem are given in Section 5. The solutions are discussed and the extended policy implications are proposed in Section 6. Section 7 concludes.

2. Literature Review

Climate change is defined as a rise in global median temperatures caused primarily by greenhouse gas emissions; this in turn increases the likelihood of extreme weather events. Human activity has caused about 1.0 °C of global warming above pre-industrial levels. This is expected to rise to 1.5 °C between 2030 and 2052 if existing emission rates continue. In 2018, the world experienced 315 cases of natural disasters, the majority of which were caused by climate change. Approximately 68.5 million people were infected, and economic losses totaled $131.7 billion, with storms, floods, wildfires, and droughts accounting for roughly 93% of the total. The economic losses attributed to wildfires in 2018 alone are nearly equal to the cumulative losses incurred from wildfires over the last decade, which is quite concerning. Moreover, the most vulnerable sectors to climate change have been identified as food, water, wellness, ecosystem, human ecosystems, and infrastructure (Fawzy et al., 2020).

Few studies examine the impact on planning regimes of rising tides, high temperatures, fires, and floods in densely populated areas. Most people around the world will be affected by climate change in the next few decades as a result of the unparalleled and rapid movement of people from rural to urban areas. Because metro cities are densely populated, and in low-lying areas, the possibilities to relocate people away from the coast are very limited (Blakely, 2007).

In urban mobility planning, the compatibilities and tensions among sustainability, climate actions, economic, political, and societal needs are widely studied in recent years. The magnitude of involvement required to mitigate and adapt to the effects of climate change will cause the action at all levels of society and government. Governments around the world will be involved in international agreements to limit total carbon emissions. Establishing carbon emission targets and standards by industry or sector, or vehicle fuel efficiency standards, has typically been the responsibility of the state and federal or regional legislatures. Policymakers, political constituencies, and stakeholders require a decision support system that explains the greenhouse consequences of urban design to make good, locally relevant land-use choices (Condon et al., 2009). Using more effective transportation systems to control gas emissions is on the agenda of governments (Okraszewska et al., 2018).

The recent drastic degradation of nature in the form of biodiversity and topsoil loss demands that institutions take action and make urgent calls to the stakeholders in the sectors that contribute to climate change. However, the preferences of the stakeholders may conflict with the climate action plans. (Foltýnová et al., 2020) Bulckaen et al. (2016) analyze the stress between stakeholders' preferences and sustainable mobility plans. They show that the sustainability rankings of the alternatives do not always match with stakeholders' preferences and the preferences of governments and targeted groups may differ from each other for some sustainability projects.

3. Problem Definition

In this section, the decision-making process is applied for the three alternatives in terms of twelve criteria. These alternatives and criteria are defined as follows:

3.1.Definition of Alternatives

A1. Zero Emission Zone Implementation: There are obvious limits to any attempt to monetize climate change, and as a result, the economic assessment should only supplement the physical impact analysis. However, complete physical impact assessment is limited to specific touchpoints and overlooks additional consequences reverberating through the economy, such as interactions, feedback, and exacerbations caused by repeated events. As a result, it is crucial to employ macroeconomic forecasts that account for general equilibrium effects and sectorial damage functions. Established macroeconomic damage estimates differ primarily in terms of how long economic loss lasts and whether climate effects are assumed to affect the growth rate or the level of the economy. First, the searcher should use empirical estimates of the relationship between temperature variations and GDP growth. This can be accomplished by down-scaling the global mean temperature change to the regional level and applying the warming effect to GDP estimations at the country level. Then, the effects of climate change are long-lasting, and observed extra adaptation is considered. Second, a quadratic damage function calibrated on the most recent estimates of global climate change effects, which reduces the GDP level with non-permanent damages, should be used. Eventually, another quadratic damage function that reproduced the forecasts from a general equilibrium model that included regional and sectorial damage functions should be observed. The three damage functions include no or few accountings of non-market damages, implying that the economic contribution is likely to be underestimated. The average climate financial benefits accrue over time and are greater for stricter temperature goals because the avoided overshoot is greater in these cases. The growth functions and the level damage functions produce qualitative and quantitatively distinct results. Due to the obvious persistence of the advantage of lower transient temperatures, the avoided effects are larger for development estimates and raise in absolute terms over time (Drouet et al., 2021).

A2. Giving Priority to Micromobility, Mobility as a Service Plan: Transportation has substantial benefits, especially as economies have become more globalized and innovative communications infrastructure has enabled low-cost international networking. People's expectations and anticipations have grown because of growing media attention to world events, more instructional and leisure opportunities, and rising income. It is hard to untangle the challenges of the interrelationships between travel, urban form, as well as sustainable development. The necessity to have some perspective of the city in its desired shape underpins the discussion–it should be sustainable (financial justification), vital (inclusive and fair), and healthy (high quality of life and environmental quality). Transport is a critical component of a city's effectiveness, vitality, and health. The EU scenario is based on sustaining the quality of urban life, urban planning, and sustainable development, with mixed uses, high densities, and good environmental conditions seen as critical to improving economic performance and the viability of cities (Banister, 2011). Sustainable mobility offers a new framework for investigating the complexities of urban centers and for strengthening the links between land use and transportation. Such urban patterns would keep actual travel lengths below the limits required for the highest use of bicycle and pedestrian modes. It would also allow for high levels of innovative services and public transportation priority, reducing the need to drive. Cities would be planned at the local level using a combination of concise strategies to allow for both great quality availability and a high-quality environment. The purpose is not to restrict the use of automobiles, as this would be challenging to attain and would be seen as violating the concepts of freedom and opportunity. The purpose is to design urban areas of such high quality and on such a tiny scale that people will not need a car. Transport policy measures, such as encouraging people to walk and cycle and developing a new transportation structure, can help decrease car use. It can be accomplished by slowing urban traffic and redistributing space to public transportation, by enforcing parking restrictions and road pricing, and by making it easier to use public transportation. Demand management is useful for restricting access, shifting space, and effectively using existing capacity (Banister, 2011).

A3. Central Planning and Optimization of Shuttle, Personnel Service, Taxi-Cab: Transportation researchers come from a variety of backgrounds, including engineering, economy, geography, planning, psychology, industry, and regional science. Transportation research, regardless of its disciplinary roots, has become extremely advanced in its use of economics. Transportation economics limits are neither well characterized nor static. Transportation economics is a branch of applied economics. It brings on and interacts with industrial engineering, economic geography, urban planning, and other disciplines, but with a slightly different focus. Engineering is concerned with facility design and implementation, whereas economics is concerned with behavioral approaches and allocation of resources. Transportation has the potential to change the character of an urban area. If transportation were free, there would be no economic reason for attendees in an economy to cluster together (Small et al., 2007). Reduced dependence on private cars has become essential as climate change quickens and gasoline prices rise. Traveling by car appears particularly inefficient when one considers that the majority of car seats on a trip are frequently empty. Ridesharing services are gaining popularity to address this inefficiency. Drivers enter their locations into their mobiles and are matched by passengers traveling in the same direction. Drivers pick up and drop off other travelers on their way to their destination, filling empty seats to save energy, decrease pollution, and split expenses. As robotic cars become more common, this process will become even more convenient (Coltin and Veloso, 2014). Taxi service is one of the most desirable modes of transportation in cities and suburbs. Taxi services have an advantage over other modes of transportation because they are easily accessible and allows you to get to your destination without pauses. There are present calls to expand taxi services in order to promote the reduction of fuel consumption from private cars in large cities. Spatial big data extracted from taxi service documents and GPS can recommend active routing options. The taxi cab ride data includes 7,000 distinct taxis operating in Seoul, South Korea. The inefficiency of incidental traveling empty taxis causes not only a waste of energy but also environmental issues such as air pollution (Yun et al., 2016).

3.2. *Definition of criteria:*

(1) Technical Aspect

C_1. Specialized personnel needs: Clusters play an important role. Clusters are geographic concentrations of economic actors, specialized distributors, service providers, firms in related industries, and affiliated institutions (e.g., institutions of higher learning, standards agencies, trade organizations) in a specialized industry that competes but also collaborates. Clusters have long been a feature of the economic landscape, with geographic concentration levels of trades and businesses in specific industries dating back centuries. The academic forefathers of clusters can be traced back to Marshall (1890/1920), who included an intriguing chapter on the externalities of industrial or commercial locations in his *Principles of Economics*. Clusters are more than just single industries; they include a variety of linked industries and other entities that are crucial to competition. Providers of specialized inputs, such as parts, machinery, and assistance, as well as

providers of specialized infrastructure, are among them. Many clusters involve governmental and other organizations that provide specialized training, education, data, research, and technical support. Trade groups and other collaborative bodies encompassing cluster participants are common in many clusters. Eventually, foreign firms are a component, but only if they invest in an important local presence on a long-term basis (Porter, 2000).

C_2. Infrastructure availability: Climate change can increase temperatures and change precipitation patterns, potentially affecting water resources. An increase in the supply of drinking water reservoirs is a critical issue. Declining infrastructure causes leaks in water distribution systems, and urbanization increases water demand in cities. One of the most significant public products is a reliable and consistent supply of drinking water. As people become more aware of climate change, there is serious concern about the future consistency of drinking water supplies. Climate change is likely to raise temperatures and change precipitation (IPCC), and recognizing the local effects on the hydrological cycle is critical for planning a reliable water supply. It was shown that the city's policy of reducing leakages to 20% would have roughly the same effect on water availability as a 10% rise in storage capability (Kristvik et al., 2018).

C_3. Concordance of the terrain of the city with the technology implementation: Since the 1987 Brundtland Report highlighted the importance of urban centers in meeting sustainable development, the ideas of sustainable cities and urban sustainability have acquired considerable traction worldwide. During the 1970s, global attention was drawn to the connections between rapid urbanization, environmental quality, and poverty, on the need for human communities to provide adequate shelter, hygiene, and local environmental quality. ‘The urban challenge’ contended that because cities will house most of the world’s future population, urban areas should be central to pursuing sustainable development (World Commission on Environment and Development, 1987). Sustainable cities are firmly embedded in the UK governance landscape, with a slew of environmental and urban policy objectives reliant on the new approach to urban advancement, not least of which is climate change mitigation. Traditionally, local funding has been a key necessity for economic success (Bulkeley and Betsill, 2005).

(2) Environmental Aspect

C_4. Carbon footprint: There are many powerful reasons why energy and ecological issues should be viewed interactively. Typically, resource economic analysis has needed to study the dynamics

of natural resource scarcity and environmental services. The current use of nonrenewable resources, such as oil reserves, helps determine resource availability in the future. Renewable natural resources regenerate in a dynamic natural ecosystem that is hampered by commercial harvesting. Equally, environmental economics must cope with carbon emissions dynamics when pollution has long-term cumulative effects on soil, marine, and atmospheric resources (Bretschger and Smulders, 2007). Personal, local, state, national, regional, and international actions all contribute to GHG. Individually, each person decides, within certain criteria, what his or her carbon footprint will be. People determine whether to walk or use a bike or a motor vehicle for transportation; if they use a motor vehicle, whether to use public, car sharing, or personal alternatives; and, if they use individual options, whether to use high or low emissions cars. Although each person's choices have a limited influence on total GHG, patterns in personal decisions amount, even on a global scale (Osofsky, 2008).

C_5*. Dependency on fossil fuels:* The global economy's experience with oil prices over the last few decades exemplifies some connections between resource dynamics and macroeconomic dynamics. The current situation is reminiscent of the 1970s and 1980s, once oil prices went up and pollution became a major political issue (Bretschger and Smulders, 2007). Human activities are increasing carbon dioxide and many other greenhouse gas emissions, expressing concern about global warming of 1–58 ° C over the next century. The latest increase in the globally averaged temperature over the last decade has seemed to be outside of the normal variations of changes in temperature over the last thousand years (Wuebbles and Jain, 2001). Fossil fuel addiction rises global temperatures will assumedly make the adverse effects of climate change more noticeable with each passing year. Furthermore, ongoing research is likely to decrease the uncertainty that many observers presently have about the magnitude of future effects (Suranovic, 2013). Hansen et al. (2012), for example, demonstrated statistical support for the idea that average global summer temperatures are higher this decade than they were in the 1950s. Studies like this one may raise awareness that the consequences of climate change are here and not just in the distant future.

C_6*. Achieving a livable city:* Cities' sustainable development is growingly recognized as critical to meeting collectively agreed-upon sustainability targets at the local, regional, and global levels, and, more broadly, to ensuring human well-being globally (Bai et al., 2016). Sustainability exemplifies yet another interaction between resource interactions on the one hand and macroeconomics dynamics on the other. After a long period of increasing awareness and shifting attitudes about the links among resource use, environmental problems, poverty, and social equality, the concept of "sustainable development" is already widely accepted as a core principle for social and environmental policies (Bretschger and Smulders, 2007). The urbanization process is one of the most significant social transitions in human history, with cities playing an incredibly prominent role in global change via a variety of social, economic, and biophysical processes at various spatial scales. Given the looming obstacles associated with increased urbanization and growth, developing resilient and sustainable cities has become extremely relevant, as recognized in Goal 11 of the United Nations Sustainable Development Goals (SDGs), which calls for making cities and residential areas encompassing, secure, adaptable, and sustainable (Bai et al., 2016).

(3) Economic aspects

C_7. Labor market efficiency: Extreme weather events are one of the mechanisms through which climate and socio-economic systems interact, and climate change is likely to change the posterior distribution of the damages they cause (Hallegatte et al., 2007). Many workers are subjected to intolerably temperature extremes in work situations that cannot be changed, and heat pressure and heat exhaustion are serious issues not only for health but also for labor productivity (Kjellstrom et al., 2009). When the body performs physical labor, heat is produced internally, which must be transmitted to the external environment to keep the body temperature from rising. Adaptive capacity will differ by country, with high-income countries adapting at a fast pace and using more expensive methods than low-income countries. Without adaptation, the financial damage from reduced labor productivity relative to the baseline can amount to up to 20% of GDP (Central America, A2, 2080). Countries' and individual businesses' willingness to take part will vary (Kjellstrom et al., 2009).

C_8. Implementation cost: While the focus on self-interest has remained, social scientists have progressively emphasized the importance of socio-cultural settings in the formation of public opinion. Public opinion is not something that “is out there” (Jasanoff, 2005), but it is influenced by a broad variety of social factors. As early as the 1950s, sociology developed socially aware ideas of public opinion that highlighted social influences. Early theories highlighted the effect of social roles and demographic characteristics on public opinion (Berelsen et al., 1954). These ideas emphasized demographic characteristics as being important for predicting an individual’s material

circumstances and information exposure, which influenced their view of their preferences and, as a result, public opinion. Throughout the 1970s and 1980s, "even sociologists who denied a strict logical decision approach recognized the concept," writes Weakliem (2005).

C_9. Regulatory revenue: Specifically, regulatory opposers use climate change's huge spatially and temporally scale to fight against national and subnational regulation. If regulatory strategies are solely based on best, international-level approaches based on nation-state permission, we will miss out on critical opportunities for invention and resource efficiency. The framework of the law presents a major challenge for effective regulation of multi-scalar issues, such as climate change. Specifically, despite the liquid scalar nature of greenhouse gas emissions and effects, the legal scales are sticky. We have split the law into governmental levels, reasonable suggestions for creating order and administration, and official regulation occurs within the resolved frames of those structures. As a result, we typically regard regulation as selecting or coordinating among those levels (Osofsky, 2008).

(4) Political and Social Aspect

C_{10}. Equity among different income groups: Nearly 5 billion of the world's 6 billion people lives in countries where the average daily income is less than $3. (World Bank, 1997). People in high-income countries get to live on 23 times that amount on typical, and the gap between the two groups is growing (World Bank, 1995). While the effects of climate change and our ability to deal with them are distributed unequally, duty for the issue is even more unequally distributed. In terms of emissions per person, poor countries continue to lag far behind us (Roberts, 2001). Most of those world's poor still collect firewood or animal waste for energy. Both cause significant damage to the environment and can contribute to changes in land use, species extinction, and climate change. However, both use "renewable" energy sources, and the greatest threats to our atmosphere come from the growth of different carbon to the biosphere caused by the combustion of fossil fuels (Kasting, 1998). To maximize the benefits of climate change mitigation regulations while minimizing their negative effects, decision-makers must know the indirect and often highly complex social and inequality effects that these policies may have, as well as the routes through which these effects emerge (Markkanen and Anger-Kraavi, 2019).

C_{11}. Public Support: Climate change policy priority structure in the United States is an interesting example to discover established theories of public opinion structure because of the scientific

discussion, ideological polarization, and parallel evolution of public opinion on climate change policy (Shwom et al., 2010). While many environmental issues have been at the core of policy discussions, almost none has been as contentious as the use of nuclear power. In the 1970s and 1980s, many scientists began discussing climate change as a possible public problem, but they received slight media attention (Miller et al., 1990)

C_{12}. Inclusiveness of disadvantaged people: While the discourse of damages raises public awareness that less developed countries and low-income populations will endure the effects of climate change, researchers have long identified that climate change risks, effects, and responses are inextricably linked to the political, social, and economic processes that create and maintain suffering. The vulnerability of low-income populations in developed countries is frequently inextricably linked to facilities and the requirement of urban services. Climate-related interruptions of urban public transportation infrastructure, for example, have been found to have a disproportional impact on low-income urban residents, who are more likely to hold hourly pay jobs and less likely to have alternative transportation options during system-wide, weather-related shutdowns. Climate change can also jeopardize most of the other central principles of reducing poverty, such as investment in infrastructure to improve food security, transportation networks, health service availability, access to markets, and access to essentials such as proper housing, potable water, and energy sources (Leichenko and Silva, 2014).

4. Proposed Methodology

4.1. Fuzzy Einstein T-norms and T-conorms

Fuzzy set theory was introduced by Zadeh (1965) to cope with uncertainties such as vagueness and ambiguities, which use the membership function to explain the knowledge. Different extensions of fuzzy sets in the literature have been presented by various researchers (Kahraman et al., 2020) such as type-2 fuzzy sets (Zadeh, 1975), rough sets (Pawlak, 1982), intuitionistic fuzzy sets (Atanassov, 1986), neutrosophic sets (Smarandache, 2003), interval type-2 fuzzy sets (Mendel et al., 2006), hesitant fuzzy sets (Torra, 2010), Pythagorean fuzzy sets (PFSs) (Yager and Abbasov, 2013), picture fuzzy sets (Cuong, 2014), q-rung Orthopair fuzzy sets (Yager, 2017), and Fermatean fuzzy sets (Senapati and Yager, 2020). These generalized fuzzy forms have been successfully adapted to various MCDM problems in the literature.

In the literature, triangular fuzzy numbers are most commonly used since they allow efficient and direct processing of uncertain information (Pamucar and Ecer, 2020; Biswas and Das, 2020; Ali et al., 2021). Triangular fuzzy numbers can be represented by the membership function $\tau_F(\xi)$: $G \rightarrow [0,1]$ as follows (Chen, 2000):

$$\tau_F(\xi) = \begin{cases} \dfrac{\xi - a}{a - c} & a \le \xi \le b \\ 1 & \xi = b \\ \dfrac{c - \xi}{c - b} & b \le \xi \le c \\ 0 & otherwise \end{cases} \tag{1}$$

where a and c denote the lower and upper bounds of the fuzzy number F, and b is the middle value for F.

Definition 1. Suppose ϕ_1 and ϕ_2 be two real numbers in F. Then the Einstein T-norm and T-conorm for ϕ_1 and ϕ_2 can be expressed, respectively, as follows (Fahmi et al., 2018):

$$t(\phi_1, \phi_2) = \frac{\phi_1 \phi_2}{1 + (1 - \phi_1)(1 - \phi_2)} \tag{2}$$

$$t^{con}(\phi_1, \phi_2) = \frac{\phi_1 + \phi_2}{1 + \phi_1 \phi_2} \tag{3}$$

where $(\phi_1, \phi_2) \in [0,1]$.

The Einstein T-norm and T-conorm, and Einstein operations with fuzzy numbers, can be defined, respectively, as follows:

Definition 2. Let $\phi_1 = (\phi_1^{(a)}, \phi_1^{(b)}, \phi_1^{(c)})$ and $\phi_2 = (\phi_2^{(a)}, \phi_2^{(b)}, \phi_2^{(c)})$ are two triangular fuzzy numbers (TFNs), and let it be $f(\phi_i) = \left(f\left(\phi_i^{(a)}\right), f\left(\phi_i^{(b)}\right), f\left(\phi_i^{(c)}\right) \right) = \left(\phi_i^{(a)} / \sum_{i=1}^{n} \phi_i^{(a)}, \phi_i^{(b)} / \sum_{i=1}^{n} \phi_i^{(b)}, \phi_i^{(c)} / \sum_{i=1}^{n} \phi_i^{(c)}, \right)$, then some operations of the Einstein T-norm and T-conorm under TFNs can be defined as follows

(1) The addition of ϕ_1 and ϕ_2 can be defined as follows:

$$\phi_1 + \phi_2 = \left(\begin{array}{l} (\phi_1^{(a)} + \phi_2^{(a)}) \dfrac{f\left(\phi_1^{(a)}\right) + f\left(\phi_2^{(a)}\right)}{1 + f\left(\phi_1^{(a)}\right) f\left(\phi_2^{(a)}\right)}, \\ (\phi_1^{(b)} + \phi_2^{(b)}) \dfrac{f\left(\phi_1^{(b)}\right) + f\left(\phi_2^{(b)}\right)}{1 + f\left(\phi_1^{(b)}\right) f\left(\phi_2^{(b)}\right)}, \\ (\phi_1^{(c)} + \phi_2^{(c)}) \dfrac{f\left(\phi_1^{(c)}\right) + f\left(\phi_2^{(c)}\right)}{1 + f\left(\phi_1^{(c)}\right) f\left(\phi_2^{(c)}\right)} \end{array} \right) \tag{4}$$

(2) The multiplication of ϕ_1 and ϕ_2 can be defined as follows:

$$\phi_1 \times \phi_2 = \left(\begin{array}{l} (\phi_1^{(a)} + \phi_2^{(a)}) \dfrac{f\left(\phi_1^{(a)}\right) f\left(\phi_2^{(a)}\right)}{1 + \left(1 - f\left(\phi_1^{(a)}\right)\right)\left(1 - f\left(\phi_1^{(a)}\right)\right)}, \\ (\phi_1^{(b)} + \phi_2^{(b)}) \dfrac{f\left(\phi_1^{(b)}\right) f\left(\phi_2^{(b)}\right)}{1 + \left(1 - f\left(\phi_1^{(b)}\right)\right)\left(1 - f\left(\phi_1^{(b)}\right)\right)}, \\ (\phi_1^{(c)} + \phi_2^{(c)}) \dfrac{f\left(\phi_1^{(c)}\right) f\left(\phi_2^{(c)}\right)}{1 + \left(1 - f\left(\phi_1^{(c)}\right)\right)\left(1 - f\left(\phi_1^{(c)}\right)\right)} \end{array} \right) \tag{5}$$

(3) Scalar multiplication, where $\varpi > 0$

$$\varpi\phi_1 = \left(\begin{array}{l} \phi_1^{(a)} \dfrac{\left(1 + f\left(\phi_1^{(a)}\right)\right)^{\varpi} - \left(1 - f\left(\phi_1^{(a)}\right)\right)^{\varpi}}{\left(1 + f\left(\phi_1^{(a)}\right)\right)^{\varpi} + \left(1 - f\left(\phi_1^{(a)}\right)\right)^{\varpi}}, \\ \phi_1^{(b)} \dfrac{\left(1 + f\left(\phi_1^{(b)}\right)\right)^{\varpi} - \left(1 - f\left(\phi_1^{(b)}\right)\right)^{\varpi}}{\left(1 + f\left(\phi_1^{(b)}\right)\right)^{\varpi} + \left(1 - f\left(\phi_1^{(b)}\right)\right)^{\varpi}}, \\ \phi_1^{(c)} \dfrac{\left(1 + f\left(\phi_1^{(c)}\right)\right)^{\varpi} - \left(1 - f\left(\phi_1^{(c)}\right)\right)^{\varpi}}{\left(1 + f\left(\phi_1^{(c)}\right)\right)^{\varpi} + \left(1 - f\left(\phi_1^{(c)}\right)\right)^{\varpi}} \end{array} \right) \tag{6}$$

(4) Power, where $\varpi > 0$

$$\phi_1^{\varpi} = \begin{pmatrix} \phi_1^{(a)} \dfrac{2f\left(\phi_1^{(a)}\right)^{\varpi}}{\left(2-f\left(\phi_1^{(a)}\right)\right)^{\varpi} + f\left(\phi_1^{(a)}\right)^{\varpi}}, \\ \phi_1^{(b)} \dfrac{2f\left(\phi_1^{(b)}\right)^{\varpi}}{\left(2-f\left(\phi_1^{(b)}\right)\right)^{\varpi} + f\left(\phi_1^{(b)}\right)^{\varpi}}, \\ \phi_1^{(c)} \dfrac{2f\left(\phi_1^{(c)}\right)^{\varpi}}{\left(2-f\left(\phi_1^{(c)}\right)\right)^{\varpi} + f\left(\phi_1^{(c)}\right)^{\varpi}} \end{pmatrix} \tag{7}$$

Definition 3. Let $\phi_j = (\phi_j^{(a)}, \phi_j^{(b)}, \phi_j^{(c)})$ $(j = 1,2,...,m)$ be a collection of TFNs, and $\omega = (\omega_1, \omega_2, \ldots, \omega_m)$ $\omega_j \in [0,1]$ be the weight coefficient of $\phi_j = (\phi_j^{(a)}, \phi_j^{(b)}, \phi_j^{(c)})$ $(j = 1,2,...,m)$ with condition that $\sum_{j=1}^{m} \omega_j = 1$. Then, fuzzy weighted averaging (FWA) operator and fuzzy weighted geometric averaging (FWGA) operator are defined, respectively, as follows (Ali et al., 2021; Youssef and Webster, 2022):

$$FWA\left(\phi_1, \phi_2, ..., \phi_m\right) = \sum_{j=1}^{m} \omega_j \phi_j = \left(\sum_{j=1}^{m} \omega_j^{(a)} \phi_j^{(a)}, \sum_{j=1}^{m} \omega_j^{(b)} \phi_j^{(b)}, \sum_{j=1}^{m} \omega_j^{(c)} \phi_j^{(c)} \right) \tag{8}$$

$$FWGA\left(\phi_1, \phi_2, .., \phi_m\right) = \prod_{j=1}^{m} \left(\phi_j\right)^{\omega_j} = \left(\prod_{j=1}^{m} \left(\phi_j^{(a)}\right)^{\omega_j^{(a)}}, \prod_{j=1}^{m} \left(\phi_j^{(b)}\right)^{\omega_j^{(b)}}, \prod_{j=1}^{m} \left(\phi_j^{(c)}\right)^{\omega_j^{(c)}} \right) \tag{9}$$

4.2. Fuzzy Einstein WASPAS Model

WASPAS method, which is one of the MCDM techniques, was developed by Zavadskas et al. (2012) in 2012. WASPAS includes the weighted sum model (WSM) and weighted product model (WPM) to provide decision-making. In this study, the classical WASPAS method is improved by integrating fuzzy Einstein operators in a fuzzy environment over triangular fuzzy numbers. It contributes to the objectification of decision-making by integrating Einstein functions into the model. The flowchart of the proposed model is shown in Fig. 1.

Let $O_i = (O_1, O_2, \cdots O_n)(i = 1, 2, \cdots, n)$ be an alternative set, $K_j = (K_1, K_2, \cdots K_m)(j = 1, 2, \cdots, m)$ be a criterion set, and $E_l = (E_1, E_2, \cdots E_e)(l = 1, 2, \cdots, e)$ be an expert set. The steps of the proposed Fuzzy Einstein WASPAS model are as follows:

Step 1. Alternatives are assessed by e experts in terms of m decision criteria using a fuzzy scale. An initial decision matrix $\psi^s = \left[\varphi_{ij}^s\right]_{n\times m}$ $(1 \le s \le e)$ is created for each expert $E_l(1 \le s \le e)$. The initial matrix ψ^{s} is transformed into fuzzy values $\tilde{\varphi}_{ij}^{s} = \left(\varphi_{ij}^{(a)s}, \varphi_{ij}^{(b)s}, \varphi_{ij}^{(c)s}\right)$ using a fuzzy linguistic scale.

Step 2. In this step, the weight coefficients of the criteria are calculated.

Step 2.1. Forming the priority vectors $\partial^{l} = \left(\nu_{K_1}^{l}, \nu_{K_2}^{l}, \ldots, \nu_{K_m}^{l}\right)$ based on expert opinions. These vectors are then assigned a fuzzy number from the scale.

Step 2.2. The absolute anti-ideal point is determined by Eq. (10).

$$\zeta_{AIP} < \left(\nu_{K_1}^{l}, \nu_{K_2}^{l}, \ldots, \nu_{K_m}^{l}\right) \tag{10}$$

Step 2.3. The ratio vector Ω^{l} of the experts $E_l = (E_1, E_2, \cdots E_e)$ is determined using Eq. (11). The relationship between the elements of the vector Θ^{l} and ζ_{AIP} is defined.

$$\phi_{K_j}^{l} = \frac{\nu_{K_j}^{l}}{\zeta_{AIP}} \tag{11}$$

, where $j = 1, 2, \cdots, m$ while $\nu_{K_j}^{l}$ denotes the element of the priority vector Θ^{l} with respect to expert $E_l = (E_1, E_2, \cdots E_e)$. The vector of the relation $\Omega^{l} = \left(\phi_{K_1}^{l}, \phi_{K_2}^{l}, .., \phi_{K_m}^{l}\right)$ for the expert is obtained.

Step 2.4. Determination of weight coefficients of criteria $\omega_j = (\omega_1, \omega_2, ..., \omega_m)^{T}$. The values of the weighting coefficients of the criteria in terms of experts are calculated using Eq. (12).

$$\omega_{j}^{l} = \frac{\ln\left(\phi_{K_j}^{l}\right)}{\ln\left(\Gamma^{l}\right)} \tag{12}$$

where $\Gamma^{l} = \prod_{j=1}^{m} \phi_{K_j}^{l}$.

Later, the aggregated fuzzy vector of weight coefficients is obtained using the fuzzy Einstein weighting function as given in Eq. (13).

$$\omega_j = \left(\begin{array}{l} \sum_{j=1}^{e}(\omega_{ij}^{(a)l})\dfrac{\prod_{j=1}^{e}\left(1+f\left(\omega_{ij}^{(a)l}\right)\right)^{1/e}-\prod_{j=1}^{e}\left(1-f\left(\omega_{ij}^{(a)l}\right)\right)^{1/e}}{\prod_{j=1}^{e}\left(1+f\left(\omega_{ij}^{(a)l}\right)\right)^{1/e}+\prod_{j=1}^{e}\left(1-f\left(\omega_{ij}^{(a)l}\right)\right)^{1/e}}, \\ \sum_{j=1}^{e}(\omega_{ij}^{(b)l})\dfrac{\prod_{j=1}^{e}\left(1+f\left(\omega_{ij}^{(b)l}\right)\right)^{1/e}-\prod_{j=1}^{e}\left(1-f\left(\omega_{ij}^{(b)l}\right)\right)^{1/e}}{\prod_{j=1}^{e}\left(1+f\left(\omega_{ij}^{(b)l}\right)\right)^{1/e}+\prod_{j=1}^{e}\left(1-f\left(\omega_{ij}^{(b)l}\right)\right)^{1/e}}, \\ \sum_{j=1}^{e}(\omega_{ij}^{(c)l})\dfrac{\prod_{j=1}^{e}\left(1+f\left(\omega_{ij}^{(c)l}\right)\right)^{1/e}-\prod_{j=1}^{e}\left(1-f\left(\omega_{ij}^{(c)l}\right)\right)^{1/e}}{\prod_{j=1}^{e}\left(1+f\left(\omega_{ij}^{(c)l}\right)\right)^{1/e}+\prod_{j=1}^{e}\left(1-f\left(\omega_{ij}^{(c)l}\right)\right)^{1/e}} \end{array} \right) \tag{13}$$

Step 3. The aggregated decision matrix $D = \left[d_{ij}\right]_{n\times m}$ is obtained by using the individual decision matrices with the help of the fuzzy Einstein weighted average (FEWAA) operator (Fahmi et al., 2018) as given in Eq. (13). $\tilde{\varphi}_{ij} = \left(\varphi_{ij}^{(a)}, \varphi_{ij}^{(b)}, \varphi_{ij}^{(c)}\right)$ is obtained using this initial decision matrix.

Step 4. The decision matrix $D = \left[d_{ij}\right]_{n\times m}$ is normalized using Eq. (14) according to the *Benefit (B)* and *Cost (C)* criteria type.

$$\tilde{\chi}_{ij} = (\chi_{ij}^{(a)}, \chi_{ij}^{(b)}, \chi_{ij}^{(c)}) = \begin{cases} \chi_{ij}^{(a)} = \dfrac{d_{ij}^{(a)}}{d_j^{+}};\ \chi_{ij}^{(b)} = \dfrac{d_{ij}^{(b)}}{d_j^{+}};\ \chi_{ij}^{(c)} = \dfrac{d_{ij}^{(c)}}{d_j^{+}} & if \quad j \in B, \\ \chi_{ij}^{(a)} = \dfrac{d_j^{-}}{d_{ij}^{(a)}};\ \chi_{ij}^{(b)} = \dfrac{d_j^{-}}{d_{ij}^{(b)}};\ \chi_{ij}^{(c)} = \dfrac{d_j^{-}}{d_{ij}^{(c)}} & if \quad j \in C. \end{cases} \tag{14}$$

$\tilde{\chi}_{ij} = (\chi_{ij}^{(a)}, \chi_{ij}^{(b)}, \chi_{ij}^{(c)})$ indicates the normalized matrix $\mho = \left[\tilde{\chi}_{ij}\right]_{n\times m}$. The elements of d_j^{+} and d_j^{-} are determined using Eqs. (15) - (16):

$$d_j^{+} = \max_{1\le j\le m}(d_{ij}^{(a)}, d_{ij}^{(b)}, d_{ij}^{(c)}) \tag{15}$$

$$d_j^{-} = \min_{1\le j\le m}(d_{ij}^{(a)}, d_{ij}^{(b)}, d_{ij}^{(c)}) \tag{16}$$

Step 5. The weighted sequences of alternatives are defined with the help of Definitions 1-3. The fuzzy Einstein WASPAS model includes two weighted sequences to compute alternative aggregation strategies. The first weighted sequence is expressed using the fuzzy Einstein weighted averaging function (WS_i), while the second weighted sequence is expressed using the fuzzy Einstein weighted geometric averaging function (WP_i) as follows:

(i) Let $(\tilde{\chi}_1, \tilde{\chi}_2, ..., \tilde{\chi}_m)$ be a set of normalized elements of the matrix $\mho = \left[\tilde{\chi}_{ij}\right]_{n\times m}$ denoted by fuzzy numbers $\tilde{\chi}_{ij} = (\chi_{ij}^{(a)}, \chi_{ij}^{(b)}, \chi_{ij}^{(c)})$, $(j = 1, 2, \cdots, m; i = 1, 2, \cdots, n)$. WS_i function can be formalized as follows:

$$WS_i = \left(WS_i^{(a)}, WS_i^{(b)}, WS_i^{(c)}\right) = \left(\begin{array}{l} \sum_{j=1}^{m} (\chi_{ij}^{(a)}) \dfrac{\prod\limits_{j=1}^{m} \left(1 + f\left(\chi_{ij}^{(a)}\right)\right)^{\omega_j^{(a)}} - \prod\limits_{j=1}^{m} \left(1 - f\left(\chi_{ij}^{(a)}\right)\right)^{\omega_j^{(a)}}}{\prod\limits_{j=1}^{m} \left(1 + f\left(\chi_{ij}^{(a)}\right)\right)^{\omega_j^{(a)}} + \prod\limits_{j=1}^{m} \left(1 - f\left(\chi_{ij}^{(a)}\right)\right)^{\omega_j^{(a)}}}, \\ \sum_{j=1}^{m} (\chi_{ij}^{(b)}) \dfrac{\prod\limits_{j=1}^{m} \left(1 + f\left(\chi_{ij}^{(b)}\right)\right)^{\omega_j^{(b)}} - \prod\limits_{j=1}^{m} \left(1 - f\left(\chi_{ij}^{(b)}\right)\right)^{\omega_j^{(b)}}}{\prod\limits_{j=1}^{m} \left(1 + f\left(\chi_{ij}^{(b)}\right)\right)^{\omega_j^{(b)}} + \prod\limits_{j=1}^{m} \left(1 - f\left(\chi_{ij}^{(b)}\right)\right)^{\omega_j^{(b)}}}, \\ \sum_{j=1}^{m} (\chi_{ij}^{(c)}) \dfrac{\prod\limits_{j=1}^{m} \left(1 + f\left(\chi_{ij}^{(c)}\right)\right)^{\omega_j^{(c)}} - \prod\limits_{j=1}^{m} \left(1 - f\left(\chi_{ij}^{(c)}\right)\right)^{\omega_j^{(c)}}}{\prod\limits_{j=1}^{m} \left(1 + f\left(\chi_{ij}^{(c)}\right)\right)^{\omega_j^{(c)}} + \prod\limits_{j=1}^{m} \left(1 - f\left(\chi_{ij}^{(c)}\right)\right)^{\omega_j^{(c)}}} \end{array} \right) \tag{17}$$

where $\omega_j = (\omega_1, \omega_2, ..., \omega_m)^T$ represents the fuzzy vector of weight coefficients of the criteria, while $f\left(\tilde{\chi}_j\right) = \left(\chi_j^{(a)} \Big/ \sum_{j=1}^{m} \chi_j^{(a)}, \chi_j^{(b)} \Big/ \sum_{j=1}^{m} \chi_j^{(b)}, \chi_j^{(c)} \Big/ \sum_{j=1}^{m} \chi_j^{(c)}\right)$.

(ii) WP_i function can be formalized as follows:

$$WP_i = \left(WP_i^{(a)}, WP_i^{(b)}, WP_i^{(c)}\right) = \left(\begin{array}{l} \sum_{j=1}^{m} (\chi_{ij}^{(a)}) \dfrac{2\prod\limits_{j=1}^{m} \left(1 + f\left(\chi_{ij}^{(a)}\right)\right)^{\omega_j^{(a)}}}{\prod\limits_{j=1}^{m} \left(2 - f\left(\chi_{ij}^{(a)}\right)\right)^{\omega_j^{(a)}} + \prod\limits_{j=1}^{m} \left(f\left(\chi_{ij}^{(a)}\right)\right)^{\omega_j^{(a)}}}, \\ \sum_{j=1}^{m} (\chi_{ij}^{(b)}) \dfrac{2\prod\limits_{j=1}^{m} \left(1 + f\left(\chi_{ij}^{(b)}\right)\right)^{\omega_j^{(b)}}}{\prod\limits_{j=1}^{m} \left(2 - f\left(\chi_{ij}^{(b)}\right)\right)^{\omega_j^{(b)}} + \prod\limits_{j=1}^{m} \left(f\left(\chi_{ij}^{(b)}\right)\right)^{\omega_j^{(b)}}}, \\ \sum_{j=1}^{m} (\chi_{ij}^{(c)}) \dfrac{2\prod\limits_{j=1}^{m} \left(1 + f\left(\chi_{ij}^{(c)}\right)\right)^{\omega_j^{(c)}}}{\prod\limits_{j=1}^{m} \left(2 - f\left(\chi_{ij}^{(c)}\right)\right)^{\omega_j^{(c)}} + \prod\limits_{j=1}^{m} \left(f\left(\chi_{ij}^{(c)}\right)\right)^{\omega_j^{(c)}}} \end{array} \right) \tag{18}$$

Step 6. The weighted aggregation (Δ) of WS_i and WP_i are computed as follows:

$$\Delta_i = \lambda \cdot WS_i + (1 - \lambda) WP_i \tag{19}$$

λ is the parameter of the WASPAS method and the range of 0–1. When the value λ is 1, the WASPAS leads to WPM, while for $\lambda = 1$, WASPAS is transformed to WSM.

Step 7. Δ_i is defuzzified by Eq. (19).

$$D_i = \frac{\Delta_i^{(a)} + 4\Delta_i^{(b)} + \Delta_i^{(c)}}{6} \tag{20}$$

Step 8. The alternatives are ranked in decreasing order according to D_i the values.

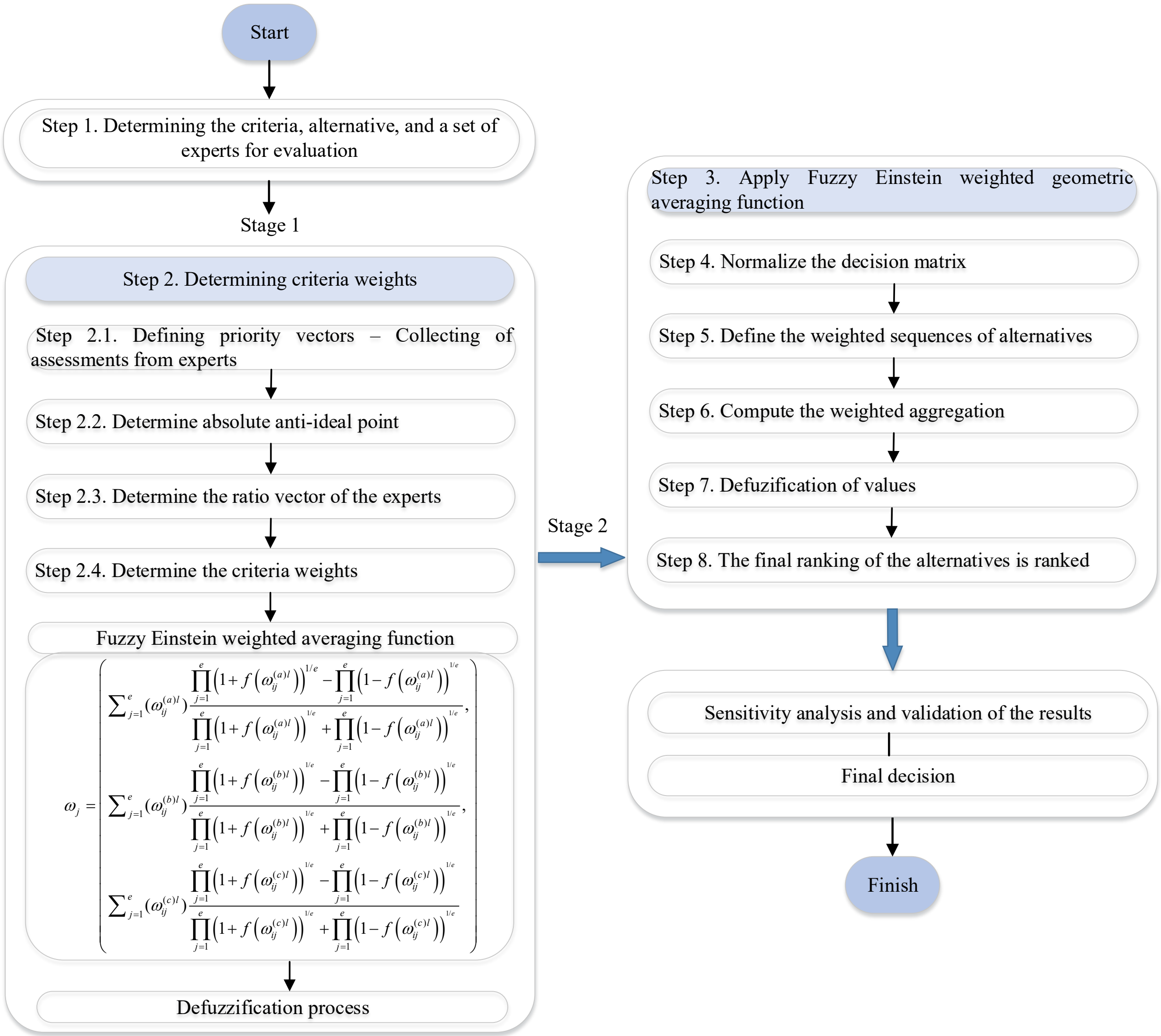


Fig.1. The flowchart of the proposed model.

5. Case Study

We consider the requirement of taking climate action for authorities in urban mobility planning. In this respect, we consider three alternative small-scale projects that the city planners can develop and implement. Public opinion is important for the implementation process. Therefore, 12 criteria reflecting the societal dynamics are grouped as technical, environmental, economic, and political. The experts' opinions from academia and business are collected. Because the problem is subject to a set of criteria that are representing conflicting dynamics, an improved WASPAS model was used in solving the decision-making problem. The results of the model and the sensitivity and the robustness analysis are as follows.

5.1. The results of the proposed model

In this study, the three alternatives and twelve evaluation criteria (see Table 1) are determined. An expert group of six decision-makers is defined.

Table 1

Proposed criteria for the evaluation of climate change mitigation strategies.

Main-criteria	**Sub-criteria**	**Types**
Technical Aspect		
C1	Specialized personnel	Cost
C2	Infrastructure availability	Benefit
C3	Concordance of the terrain of the city with the technology implementation	Benefit
Environmental Aspect		
C4	Carbon footprint	Cost
C5	Dependency on fossil fuels	Cost
C6	Achieving a livable city	Benefit
Economic Aspects		
C7	Labor market efficiency	Benefit
C8	Implementation cost	Cost
C9	Regulatory revenue	Benefit
Political and Social Aspect		
C10	Equity among different income groups	Benefit
C11	Public Support	Benefit
C12	Inclusiveness of disadvantaged people	Benefit

Step 1: Three alternatives are evaluated by six experts in terms of each criterion with the help of the linguistic terms listed in Table 2 and the decision matrix is constructed. The linguistic evaluations regarding experts' opinions are reported in Table 3.

Table 2

Linguistic terms and their fuzzy numbers for evaluating alternatives (Rakhmangulov et al., 2019).

Linguistic terms	Membership function
Absolutely low (AL)	(1, 1, 1)
Very low (VL)	(1, 2, 3)
Low (L)	(2, 3, 4)
Medium low (ML)	(3, 4, 5)

Equal (E)	(4, 5, 6)
Medium high (MH)	(5, 6, 7)
High (H)	(6, 7, 8)
Very high (EH)	(7, 8, 9)
Absolutely high (AH)	(8, 9, 9)

Table 3
Linguistic evaluations of the decision-makers for the alternatives.

Crit.	A_1	A_2	A_3
C_1	EH; H; E; L; AL; E	H; EH; H; VL; VL; MH	ML; AL; AH; AL; ML; H
C_2	EH; MH; AH; EH; AH; EH	AH; E; MH; AH; E; H	VL; EH; L; ML; ML; AH
C_3	VL; E; EH; AH; H; EH	AH; ML; AH; EH; AH; AH	AL; H; H; H; L; L
C_4	AL; VL; AH; AL; AL; AL	VL; AL; E; L; ML; L	ML; L; EH; VL; L; VL
C_5	VL; EH; AL; AL; VL; AL	AL; AH; L; L; L; VL	EH; L; E; ML; E; ML
C_6	H; AH; AH; AH; AH; AH	EH; H; EH; E; H; MH	MH; EH; MH; EH; EH; H
C_7	E; VL; L; ML; MH; E	VL; ML; H; H; E; L	AL; AH; EH; AH; AH; AH
C_8	L; EH; AL; L; VL; ML	L; H; VL; ML; L; E	AH; VL; H; H; ML; EH
C_9	AH; E; H; AH; H; AH	AL; MH; EH; H; MH; EH	AL; EH; MH; EH; E; H
C_{10}	L; ML; H; E; E; EH	H; E; AH; H; MH; ML	H; EH; EH; EH; EH; AH
C_{11}	L; H; MH; EH; EH; EH	ML; AH; H; H; AH; MH	MH; EH; AH; AH; H; AH
C_{12}	VL; ML; E; MH; MH; H	AL; L; ML; E; L; E	AH; EH; AH; H; AH; EH

Step 2: Calculation of weight coefficients of criteria.

Step 2.1: The priority vectors for the twelve criteria are formed by experts. Later, these vectors are transformed into the corresponding fuzzy numbers using Table 4 and are reported in Table 5.

Table 4
Fuzzy scale for evaluating criteria.

Linguistic terms	Membership function
Very low (VL)	(1, 1, 2)
Low (L)	(1, 2, 3)
Medium (M)	(2, 3, 4)
High (H)	(3, 4, 5)
Very high (EH)	(4, 5, 5)

Table 5
The priority vectors of the twelve criteria for each expert.

Experts	Expert 1	Expert 2	Expert 3	Expert 4	Expert 5	Expert 6
C1	M	M	H	M	VH	H
C2	H	M	VH	VH	H	H

C3	H	L	H	M	H	VH
C4	M	VH	H	VH	M	VH
C5	M	H	M	H	L	H
C6	H	VH	VH	VH	H	H
C7	L	M	M	L	H	VH
C8	VH	L	H	VH	VH	H
C9	VH	M	L	M	VH	H
C10	L	L	VH	H	M	H
C11	VH	H	L	M	M	H
C12	H	H	VH	VH	H	VH

Step 2.2. Absolute anti-ideal point $\gamma_{AIP} = (0.4, 0.5, 0.6)$ is determined using Eq. (10).

Step 2.3. The vectors of the ratio Ω^l, $(1 \le l \le 6)$ are determined using Eq. (11) for each expert, as given in Table 6.

Table 6
The vectors of the ratio.

Criteria	E_1	E_2	E_3	E_4	E_5	E_6
C_1	(3.33,6,10)	(3.33,6,10)	(5,8,12.5)	(3.33,6,10)	(6.67,10,12.5)	(5,8,12.5)
C_2	(5,8,12.5)	(3.33,6,10)	(6.67,10,12.5)	(6.67,10,12.5)	(5,8,12.5)	(5,8,12.5)
C_3	(5,8,12.5)	(1.67,4,7.5)	(5,8,12.5)	(3.33,6,10)	(5,8,12.5)	(6.67,10,12.5)
C_4	(3.33,6,10)	(6.67,10,12.5)	(5,8,12.5)	(6.67,10,12.5)	(3.33,6,10)	(6.67,10,12.5)
C_5	(3.33,6,10)	(5,8,12.5)	(3.33,6,10)	(5,8,12.5)	(1.67,4,7.5)	(5,8,12.5)
C_6	(5,8,12.5)	(6.67,10,12.5)	(6.67,10,12.5)	(6.67,10,12.5)	(5,8,12.5)	(5,8,12.5)
C_7	(1.67,4,7.5)	(3.33,6,10)	(3.33,6,10)	(1.67,4,7.5)	(5,8,12.5)	(6.67,10,12.5)
C_8	(6.67,10,12.5)	(1.67,4,7.5)	(5,8,12.5)	(6.67,10,12.5)	(6.67,10,12.5)	(5,8,12.5)
C_9	(6.67,10,12.5)	(3.33,6,10)	(1.67,4,7.5)	(3.33,6,10)	(6.67,10,12.5)	(5,8,12.5)
C_{10}	(1.67,4,7.5)	(1.67,4,7.5)	(6.67,10,12.5)	(5,8,12.5)	(3.33,6,10)	(5,8,12.5)
C_{11}	(6.67,10,12.5)	(5,8,12.5)	(1.67,4,7.5)	(3.33,6,10)	(3.33,6,10)	(5,8,12.5)
C_{12}	(5,8,12.5)	(5,8,12.5)	(6.67,10,12.5)	(6.67,10,12.5)	(5,8,12.5)	(6.67,10,12.5)

Step 2.4: The fuzzy vectors of weight coefficients for each criterion are calculated using Eqs. (12)-(13). The local values are defuzzified using Eq. (20) and presented in Table 7.

Table 7
The local values and crisp criteria weights.

Criteria	Local values	Weights
C_1	(0.05,0.082,0.138)	0.0864
C_2	(0.057,0.088,0.142)	0.0918
C_3	(0.048,0.081,0.137)	0.0852

C_4	(0.056,0.088,0.141)	0.0912
C_5	(0.045,0.078,0.136)	0.0823
C_6	(0.061,0.092,0.145)	0.0955
C_7	(0.04,0.075,0.13)	0.0782
C_8	(0.054,0.087,0.139)	0.0900
C_9	(0.048,0.081,0.135)	0.0848
C_{10}	(0.042,0.077,0.132)	0.0801
C_{11}	(0.046,0.08,0.136)	0.0837
C_{12}	(0.061,0.092,0.145)	0.0953

Step 3. Linguistic information provided by six experts is converted into fuzzy numbers using Table 2. Later, each expert's opinions are aggregated in one decision matrix using the fuzzy Einstein weighting function given in Eq. (13), and the aggregated decision matrix is presented in Table 8.

Table 8
The aggregated decision matrix.

Criteria	A1	A2	A3
C_1	(4.03,4.86,5.7)	(4.37,5.36,6.36)	(3.73,4.4,4.89)
C_2	(7,8,8.67)	(5.85,6.85,7.51)	(4.05,5.04,5.86)
C_3	(5.53,6.52,7.35)	(7.01,8.01,8.34)	(3.87,4.7,5.54)
C_4	(2.36,2.71,2.84)	(2.18,3.02,3.85)	(2.73,3.71,4.7)
C_5	(2.15,2.63,3.13)	(2.78,3.58,4.22)	(3.86,4.85,5.85)
C_6	(7.67,8.67,8.83)	(5.84,6.84,7.84)	(6.17,7.17,8.17)
C_7	(3.18,4.18,5.18)	(3.69,4.69,5.68)	(6.69,7.52,7.69)
C_8	(2.73,3.55,4.38)	(3.03,4.02,5.02)	(5.2,6.19,7.02)
C_9	(6.68,7.67,8.17)	(5.19,6.02,6.86)	(5.02,5.86,6.69)
C_{10}	(4.35,5.35,6.35)	(5.35,6.35,7.17)	(7,8,8.83)
C_{11}	(5.68,6.68,7.68)	(6.01,7.01,7.67)	(7.01,8,8.5)
C_{12}	(4.02,5.01,6.01)	(2.68,3.51,4.35)	(7.34,8.34,8.83)

As an example for Alternative A_1-Criterion C_1, the calculation of the fuzzy Einstein weighting function is presented to combine the expert opinions. With the help of Tables 4 and 5, expert opinions are expressed as follows: $\varphi_{11}^{1}=(7,8,9)$, $\varphi_{11}^{2}=(6,7,8)$, $\varphi_{11}^{3}=(4,5,6)$, $\varphi_{11}^{4}=(2,3,4)$, $\varphi_{11}^{5}=(1,1,1)$, and $\varphi_{11}^{6}=(4,5,6)$, where $\omega_r=1/6\ (r=1,2,\ldots,6)$. After that, the fuzzy Einstein weighting function is applied for A_1- C_1:

$$EWA\left(\tilde{\varphi}_{11}\right)=$$

$$\begin{cases}
\varphi_{11}^{(a)}=\begin{pmatrix}7+6+4+\\2+1+4\end{pmatrix}\dfrac{\begin{pmatrix}(1+0.29)^{0.17}\cdot(1+0.25)^{0.17}\cdot\\(1+0.17)^{0.17}\cdot\ldots\cdot(1+0.17)^{0.17}\end{pmatrix}-\begin{pmatrix}(1-0.29)^{0.17}\cdot(1-0.25)^{0.17}\cdot\\(1-0.17)^{0.17}\cdot\ldots\cdot(1-0.17)^{0.17}\end{pmatrix}}{\begin{pmatrix}(1+0.29)^{0.17}\cdot(1+0.25)^{0.17}\cdot\\(1+0.17)^{0.17}\cdot\ldots\cdot(1+0.17)^{0.17}\end{pmatrix}+\begin{pmatrix}(1-0.29)^{0.17}\cdot(1-0.25)^{0.17}\cdot\\(1-0.17)^{0.17}\cdot\ldots\cdot(1-0.17)^{0.17}\end{pmatrix}}\\
\varphi_{11}^{(b)}=\begin{pmatrix}8+7+5+\\3+1+5\end{pmatrix}\dfrac{\begin{pmatrix}(1+0.28)^{0.17}\cdot(1+0.24)^{0.17}\cdot\\(1+0.17)^{0.17}\cdot\ldots\cdot(1+0.17)^{0.17}\end{pmatrix}-\begin{pmatrix}(1-0.28)^{0.17}\cdot(1-0.24)^{0.17}\cdot\\(1-0.17)^{0.17}\cdot\ldots\cdot(1-0.17)^{0.17}\end{pmatrix}}{\begin{pmatrix}(1+0.28)^{0.17}\cdot(1+0.24)^{0.17}\cdot\\(1+0.17)^{0.17}\cdot\ldots\cdot(1+0.17)^{0.17}\end{pmatrix}+\begin{pmatrix}(1-0.28)^{0.17}\cdot(1-0.24)^{0.17}\cdot\\(1-0.17)^{0.17}\cdot\ldots\cdot(1-0.17)^{0.17}\end{pmatrix}}\\
\varphi_{11}^{(c)}=\begin{pmatrix}9+8+6+\\4+1+6\end{pmatrix}\dfrac{\begin{pmatrix}(1+0.26)^{0.17}\cdot(1+0.24)^{0.17}\cdot\\(1+0.18)^{0.17}\cdot\ldots\cdot(1+0.18)^{0.17}\end{pmatrix}-\begin{pmatrix}(1-0.26)^{0.17}\cdot(1-0.24)^{0.17}\cdot\\(1-0.18)^{0.17}\cdot\ldots\cdot(1-0.18)^{0.17}\end{pmatrix}}{\begin{pmatrix}(1+0.26)^{0.17}\cdot(1+0.24)^{0.17}\cdot\\(1+0.18)^{0.17}\cdot\ldots\cdot(1+0.18)^{0.17}\end{pmatrix}+\begin{pmatrix}(1-0.26)^{0.17}\cdot(1-0.24)^{0.17}\cdot\\(1-0.18)^{0.17}\cdot\ldots\cdot(1-0.18)^{0.17}\end{pmatrix}}
\end{cases}$$

$$=\left(4.03,4.86,5.70\right)$$

Similarly, the aggregated values of six experts for the remaining alternative in terms of criteria are calculated as given in Table 8.

Step 4. This step is to calculate the normalized decision matrix, as presented in Table 9. Using the initial decision matrix, we calculate the normalized decision matrix for three alternatives using Eqs. (14)-(16). For example, the normalized value of alternative A$_1$ with respect to C$_1$ is as follows:

$$\tilde{\chi}_{11}=(\chi_{11}^{(a)},\chi_{11}^{(b)},\chi_{11}^{(c)})=\begin{cases}\chi_{11}^{(a)}=\dfrac{d_{C1}^{-}}{d_{11}^{(a)}}=\dfrac{3.73}{5.70}=0.65;\\[2ex]\chi_{11}^{(b)}=\dfrac{d_{C1}^{-}}{d_{11}^{(b)}}=\dfrac{3.73}{4.86}=0.77;\\[2ex]\chi_{11}^{(c)}=\dfrac{d_{C1}^{-}}{d_{11}^{(c)}}=\dfrac{3.73}{4.03}=0.92.\end{cases}$$

$$=\left(0.65,0.77,0.92\right)$$

Similarly, the normalized values of three alternatives for the remaining criteria are calculated as given in Table 9.

Table 9
The fuzzy normalized decision matrix.

Criteria	A$_1$	A$_2$	A$_3$
C$_1$	(0.654,0.766,0.924)	(0.586,0.695,0.853)	(0.762,0.848,1)

C_2	(0.808,0.923,1)	(0.675,0.79,0.866)	(0.468,0.582,0.676)
C_3	(0.662,0.782,0.881)	(0.841,0.96,1)	(0.464,0.564,0.664)
C_4	(0.769,0.807,0.924)	(0.567,0.724,1)	(0.465,0.588,0.799)
C_5	(0.687,0.816,1)	(0.509,0.6,0.774)	(0.367,0.443,0.557)
C_6	(0.868,0.981,1)	(0.661,0.774,0.887)	(0.698,0.812,0.925)
C_7	(0.414,0.543,0.673)	(0.48,0.61,0.739)	(0.87,0.978,1)
C_8	(0.624,0.77,1)	(0.545,0.68,0.902)	(0.39,0.442,0.526)
C_9	(0.817,0.939,1)	(0.635,0.737,0.839)	(0.615,0.717,0.819)
C_{10}	(0.493,0.606,0.718)	(0.605,0.718,0.812)	(0.793,0.906,1)
C_{11}	(0.668,0.786,0.903)	(0.707,0.825,0.903)	(0.824,0.942,1)
C_{12}	(0.455,0.568,0.681)	(0.303,0.398,0.492)	(0.83,0.944,1)

Step 5. The fuzzy Einstein weighted averaging function (WS_i) and geometric averaging function (WP_i) for each alternative are calculated using Eqs. (17) and (18) and presented in Table 10.

Table 10

The values of WS_i and WP_i.

Alternatives	WS_i			WP_i		
A_1	0.664	0.778	1.480	0.648	0.765	0.815
A_2	0.592	0.708	1.389	0.575	0.693	0.729
A_3	0.627	0.728	1.375	0.599	0.701	0.704

Step 6. The weighted aggregation (Δ) of WS_i and WP_i are calculated using Eq. (19).

$$\Delta_i = \begin{array}{c} A_1 \\ A_2 \\ A_3 \end{array} \begin{bmatrix} 0.656 & 0.771 & 1.148 \\ 0.583 & 0.701 & 1.059 \\ 0.613 & 0.715 & 1.039 \end{bmatrix}$$

For example, the weighted aggregation of WS_1 and WP_1 for the alternative A_1 is calculated as follows:

$$\Delta_1^a = (0.5)\cdot 0.664 + (1-0.5)\cdot 0.65 = 0.656$$
$$\Delta_1^b = (0.5)\cdot 0.778 + (1-0.5)\cdot 0.76 = 0.771$$
$$\Delta_1^c = (0.5)\cdot 1.480 + (1-0.5)\cdot 0.82 = 1.148$$

Steps 7-8. The aggregated values (Δ) are defuzzified using Eq. (20). Later, the alternatives are ranked according to score values.

$$\begin{array}{c} \\ A_1 \\ A_2 \\ A_3 \end{array}\begin{array}{cc} D_i & Rank \\ \begin{bmatrix} 0.815 \\ 0.741 \\ 0.752 \end{bmatrix} & \begin{bmatrix} 1 \\ 3 \\ 2 \end{bmatrix} \end{array}$$

According to D_i, the final ranking is $A_1 > A_3 > A_2$. Based on the results, A_1 is preferred to A_3 and A_2.

5.2. Sensitivity Analysis and Validation

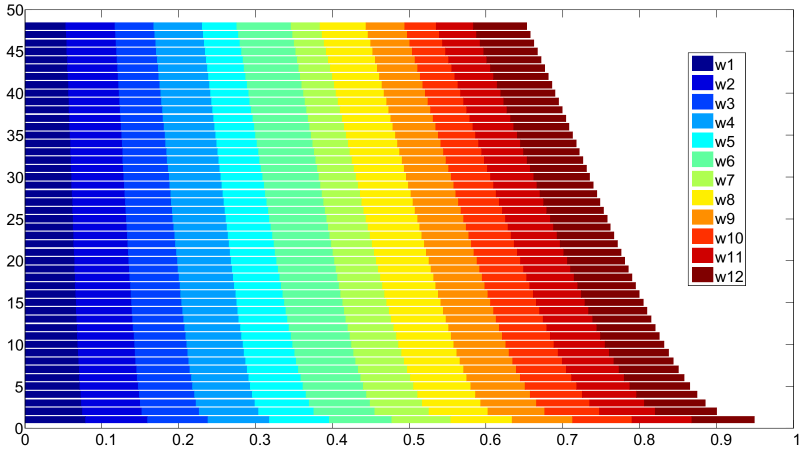
In most of the multi-criteria models, some parameters are determined based on the subjective preferences of the decision-maker. Such parameters depend on the conditions in which the system is modeled and the decision maker's perception. Since the change of subjectively defined parameters can cause disturbance of the stability of the initial solution, it is necessary to perform the sensitivity analysis and stability of the solution. Sensitivity analysis presets a simulation of the change of these parameters in the corresponding interval. Such an analysis enables the consideration of the influence of subjective parameters on the final results of the model, i.e., it allows the verification of the robustness of the results of the multi-criteria model.

The following parameters were used to analyze the sensitivity of the fuzzy Einstein WASPAS methodology: a) Absolute anti-ideal point (ζ_{AIP}) which was used to calculate the weight coefficients of the criteria; b) Weighting coefficients of experts (w_j^{DM}) who participated in the study and c) Parameter λ used for fusion of fuzzy Einstein functions. After the analysis of subjectively defined parameters, the results of the fuzzy Einstein WASPAS model were compared with other fuzzy MCDM techniques. The following section presents the sensitivity analysis of the Fuzzy Einstein WASPAS model.

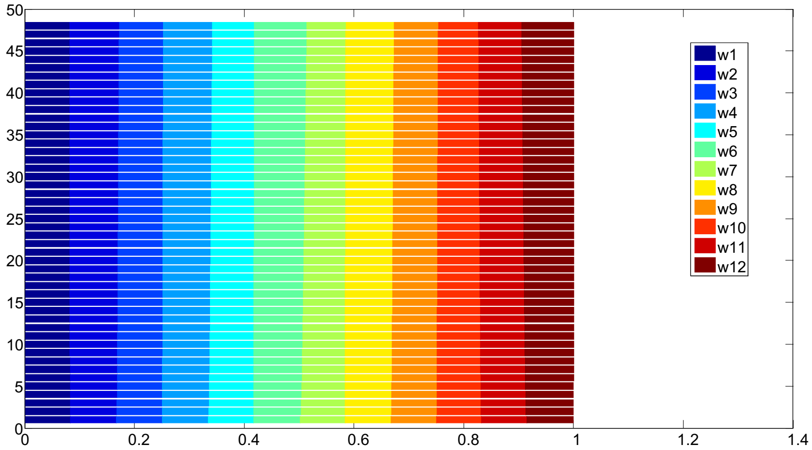
a) *Simulation changes absolute anti-ideal point (*ζ_{AIP}*)*

The absolute anti-ideal point (AAIP) was used to define the reference relationships between expert assessments when calculating the weighting coefficients of the criteria. It is a subjectively defined parameter that is determined from the interval $0 < \zeta_{AIP} < 1$. The value $\zeta_{AIP} = (0.4, 0.5, 0.6)$ was adopted for the calculation of the initial fuzzy vector of weight coefficients. Since AAIP can have any value from the interval $0 < \zeta_{AIP} < 1$, it is necessary to answer the question: *Do other values of* w_j *affect the change in the initial solution*?

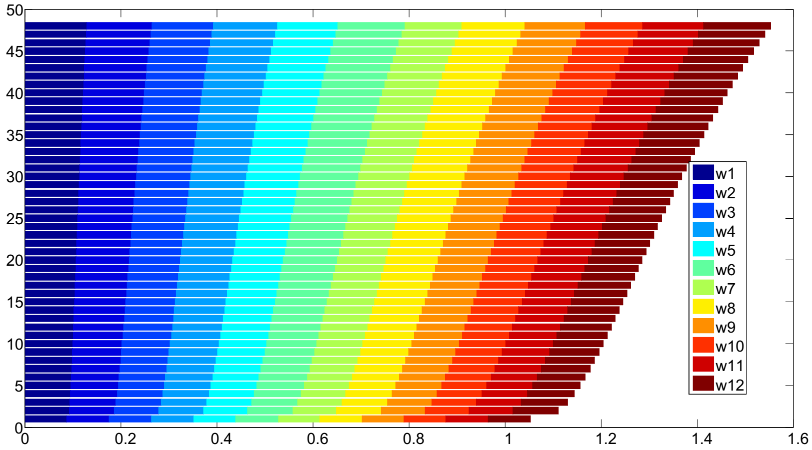
A simulation of AAIP change was performed in the following section to answer this question. Fifty scenarios with new vectors of weighting coefficients were formed. In the first scenario, the value $\zeta_{AIP} = 0.01$ is adopted, while in each subsequent scenario, AAIP is defined using the following expression $\zeta_{AAIP}^{s} = \zeta_{AAIP}^{s-1} + 0.02$, where s denotes the number of scenarios. Thus, for each new AAIP value, a new fuzzy vector of weight coefficients is created in Fig. 2.



a) Scenarios for left value $w_j^{(l)}$



b) Scenarios for modal value $w_j^{(m)}$



c) Scenarios for upper value $w_j^{(u)}$

Fig. 2. Influence of AAIP on the change of weight coefficients of criteria.

The results in Fig. 2 indicate interdependence between the adopted AAIP reference value and the criterion weighting coefficients. Therefore, in the following, the influence of new vectors of weight coefficients of the criteria on the change of the initial solution is analyzed. For each new vector of weight coefficients of the criteria, new score values of alternatives are defined in Fig. 3.

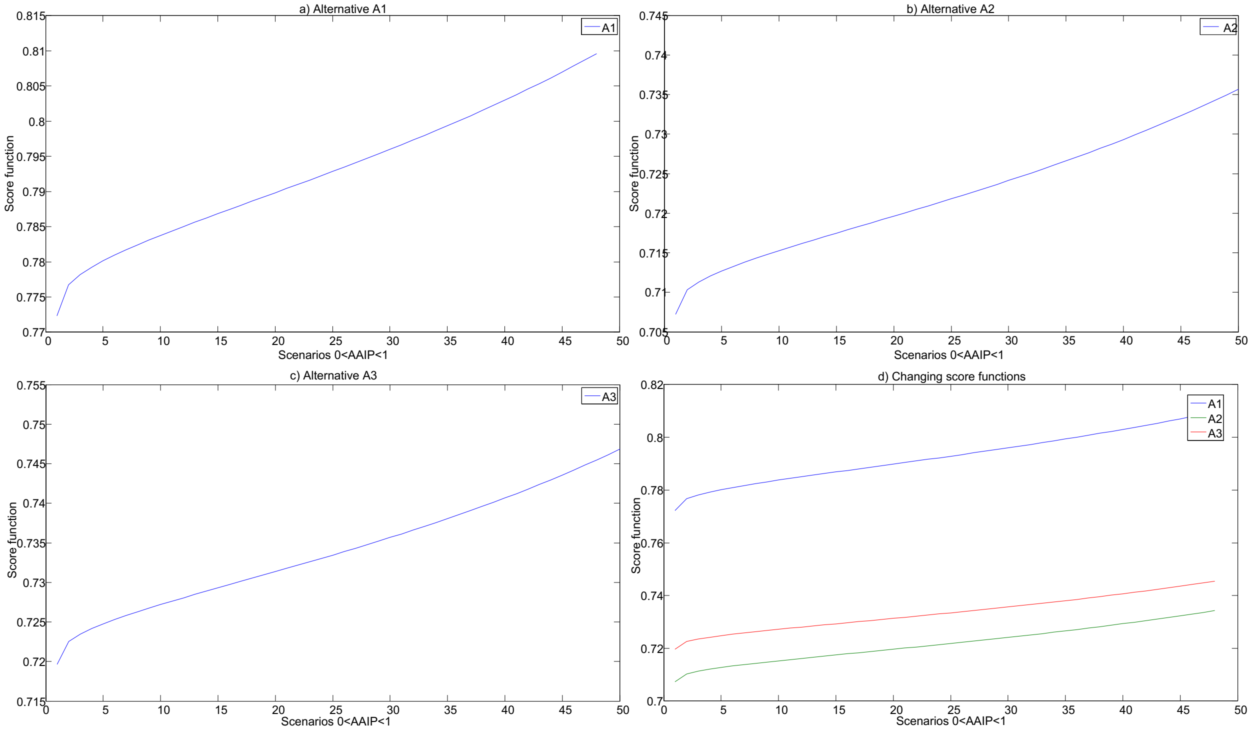


Fig. 2. Impact of AAIP on change score values alternative.

The results from Fig. 3 (a-c) show that an increase in AAIP leads to increasing score values of all three alternatives. Also, the results in Fig. 3 (d) show no extreme changes in the score values of the alternatives that could disrupt the initial ranking. Therefore, based on the presented analysis, we can conclude that alternative A_1 is the dominant solution and that the initial is credible.

b) *Simulation of changes in expert weights* (w_j^{DM})

The research presented in this paper involved six experts who evaluated alternatives. The fuzzy weighted Einstein function was used to aggregate expert preferences in the home matrix. When aggregating the export preferences, the same value of the weighting coefficient $w_j^{DM} = 1/6 = 0.1667$ (j=1,2,…,6) was adopted for all experts.

It is indisputable that the results of multi-criteria models depend on the values of the experts' weight coefficients, so their influence on the final results of the model is analyzed in the following part. In the experiment presented in the following section, the change in the weight coefficient of the first expert in the interval $w_1^{DM} = [0.0017, 0.1650]$ was simulated. Simultaneously, with the change in the weighting coefficient w_1^{DM}, the change in the weighting coefficients of the remaining experts in the interval $0.1670 \le w_j^{DM} \le 0.1997$ ($j = 2,3,...,6$) was simulated. The left limit value of the weight coefficient interval w_1^{DM} is defined by reducing the initial value by 99%, while the right limit value is defined by reducing the initial value by 1%. The interval $w_1^{DM} = [0.0017, 0.1650]$ is divided into 21 scenarios. In the first scenario, the initial value of the weighting coefficient w_1^{DM} was reduced by 1%, while in each subsequent scenario, the value w_1^{DM} was reduced by 5%. At the same time, the weight coefficients of the remaining experts were corrected by applying the expression $w_j^{DM'} = w_j^{DM}(1 - w_1^{DM}) / (1 - w_1^{DM'})$, where w_j^{DM} represents the initial value of the expert weighting factor, while $w_1^{DM'}$ represents the corrected value of the first expert weighting factor. Thus, a set of new vectors of expert weight coefficients was formed (see Fig. 4).

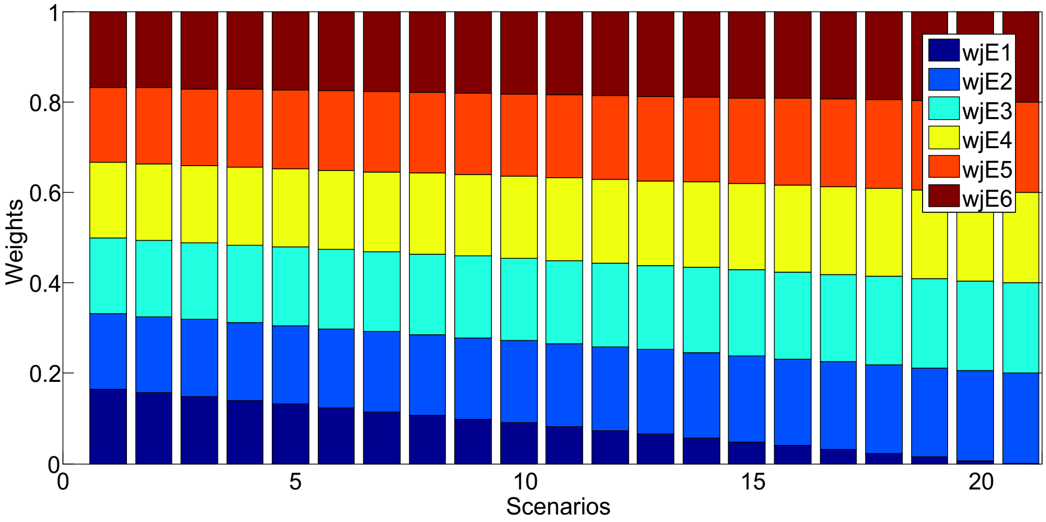


Fig. 4. Graphical representation of new vectors of expert weight weights.

New vector weights of expert weights were used to aggregate expert preferences in the home matrix. In the following section, the influence of new vectors of weight coefficients on the change of score values of alternatives are analyzed in Fig. 5.

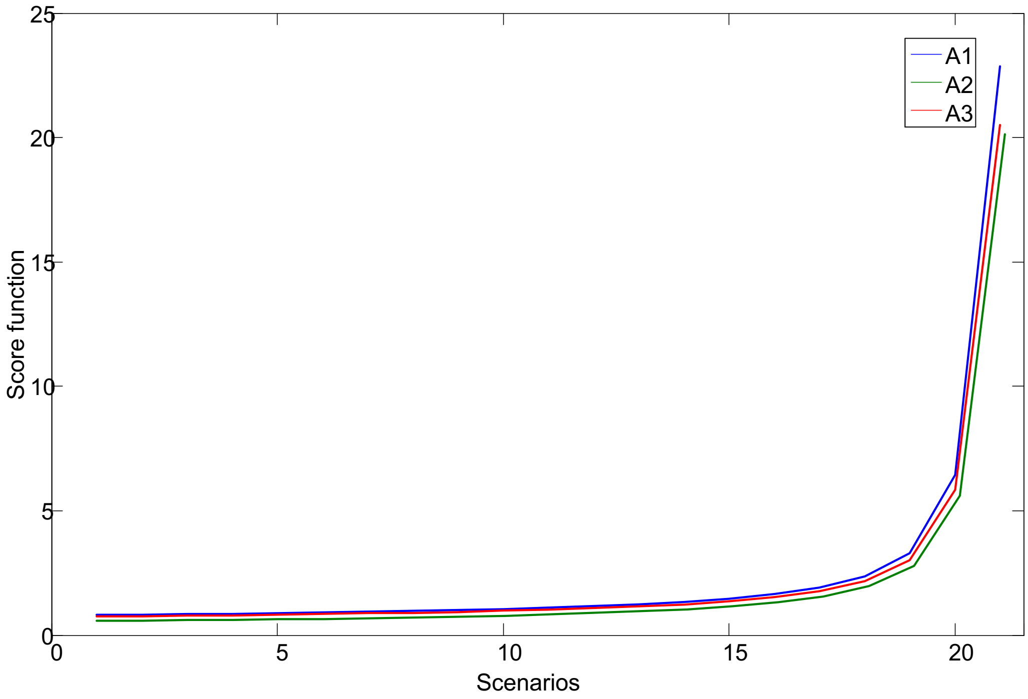


Fig. 5. Influence of change of expert weight coefficients on change of score values of alternatives.

The score values of the alternatives shown in Fig. 5 show that the new weights vectors significantly impact defining the initial solution. Also, the results from Fig. 5 show that the model is sensitive to changes in input parameters. A similar simulation was performed for the weighting coefficients of other experts. Six simulations were performed, and 21 scenarios were generated within each simulation. In all six simulations, similar results were obtained, confirming the dominance of alternative A_1 remaining dominant. At the same time, the ranking of the remaining alternatives (A_3 and A_2) was confirmed.

c) Simulation of parameter change λ

The parameter λ was used to fuse fuzzy Einstein functions in the WASPAS method. Based on Eq. (19), we can conclude that the parameter λ has a significant impact on the definition of the final score values of alternatives, and thus on the final decision. To analyze the influence of this parameter on the initial solution, its change in the interval $0 \leq \lambda \leq 1$ was simulated. Fifty scenarios were formed and the dependence of score values of alternatives on the parameter λ was analyzed. In the first scenario, the value $\lambda = 0.0$ was adopted, while in each subsequent scenario, the value of λ was increased by 0.02. The influence of the parameter λ on the change of the utility functions is shown in Fig. 6.

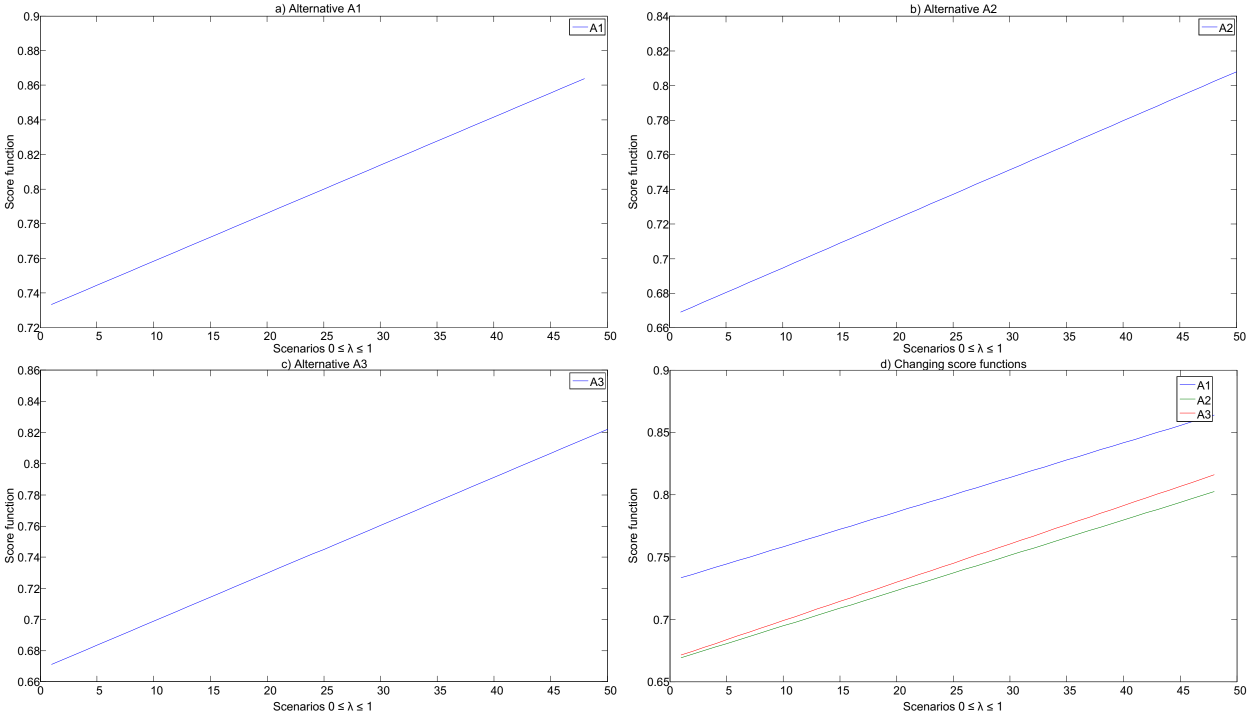


Fig. 6. The analysis of the influence of the parameter λ.

Based on the results from Fig. 6, we can conclude that the parameter λ affects the change in the score values of the alternatives. Also, the results from Fig. 6 show a significant dominance of alternative A$_1$ in the considered set, so changes in the parameter λ do not lead to a violation of the initial rank.

d) Comparison of results of fuzzy Einstein WASPAS models and other MCDM models

Numerous studies in the literature show that applying different normalization techniques in MCDM methods can lead to rank impairment. Such changes result in different dispositions of natural and normalized attribute values (Zolfani et al., 2020; Pamucar and Savin, 2020; Aytekin, 2021; Mukhametzyanov, 2021). To overcome such problems, to confirm the results the authors suggest the use of normalization techniques with similar characteristics (Mukhametzyanov and Pamucar, 2018). Since the fuzzy Einstein WASPAS method for data, normalization uses the linear max normalization technique, fuzzy methodologies using a group of linear data normalization techniques were selected for comparison, as follows: fuzzy COPRAS (Dhiman and Deb, 2020) and fuzzy (Ghorabaee et al., 2016) model using the linear sum normalization technique, fuzzy MABAC

(Liang et al., 2019) model using linear max-min normalization technique, fuzzy and fuzzy MULTIMOORA (Karamaşa et al., 2021) model using linear max normalization technique. After applying these models, the results shown in Fig. 7 were obtained.

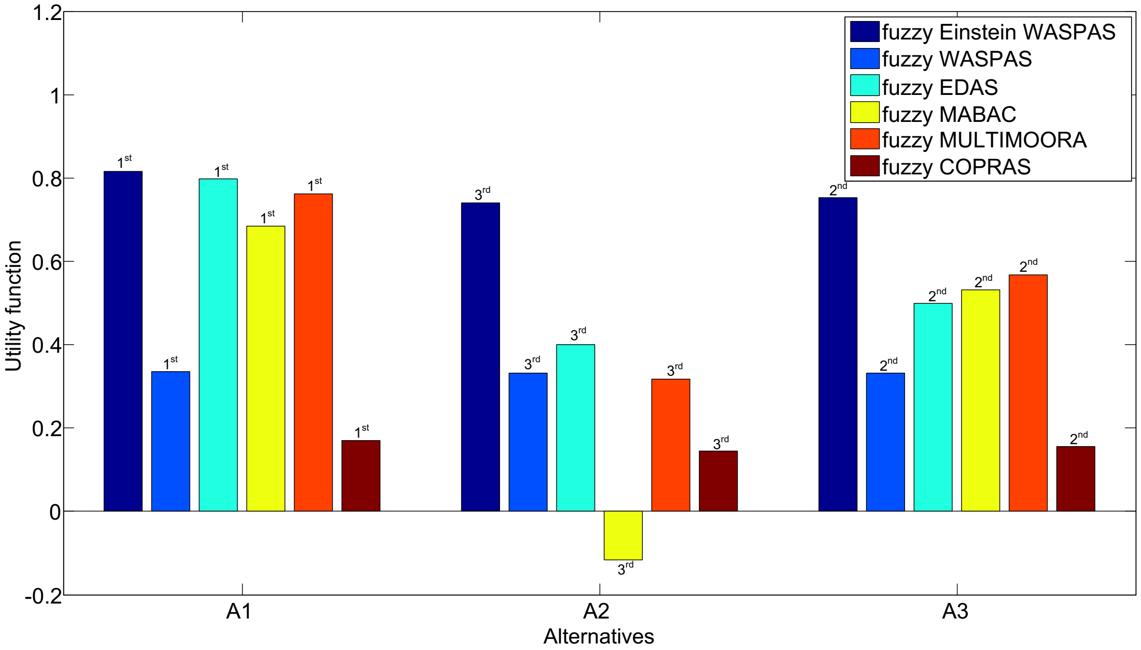


Fig. 7. Ranks of the alternatives based on different MCDM techniques.

The results from Fig. 7 show that all considered fuzzy multi-criteria techniques suggest the same range of alternatives, i.e., A_1> A_3> A_2. The comparative analysis (see Fig. 7) proves the robustness of the fuzzy Einstein WASPAS methodology results and that the proposed choice of alternative A_1 is credible. In the following, certain specifics of the considered multi-criteria techniques are analyzed in Table 11.

Table 11
The comparisons of different methods.

MCDM methodology	Possibility of determining weight coefficients of criteria	Flexible decision making due to decision makers' risk attitude	Flexibility in real world applications	Clearly defined rank alternative	Characteristics of functions for defining weighted sequences
Fuzzy Einstein WASPAS (Proposed)	Yes	Yes	Yes	Yes	Nonlinear form
Fuzzy WASPAS	No	Yes	Partially	Yes	Linear form

fuzzy EDAS (Ghorabaee et al., 2016)	No	No	No	Yes	Linear form
Fuzzy MABAC (Liang et al., 2019)	No	No	No	Yes	Linear form
Fuzzy MULTIMOORA (Karamaşa et al., 2021)	No	No	No	Yes	Linear form
Fuzzy COPRAS (Dhiman and Deb, 2020)	No	No	No	Yes	Linear form

The aggregation functions in the presented fuzzy MCDM models are linear, while in the fuzzy Einstein WASPAS methodology, the nonlinear fuzzy Einstein aggregation functions are used. Fuzzy Einstein aggregation functions have been used to allow flexible decision-making and present a nonlinear relationship between home matrix arguments. Also, fuzzy Einstein aggregation functions enable flexible decision-making due to decision-makers' risk attitudes. Therefore, the presented multi-criteria framework is more general and flexible than traditional fuzzy techniques. This feature of the fuzzy Einstein WASPAS methodology provides the possibility of its wide application in the processing of uncertain information in a dynamic environment.

In most traditional fuzzy MCDM techniques, including fuzzy EDAS, fuzzy MABAC, fuzzy MULTIMOORA, and COPRAS, it is necessary to mathematically formulate the aggregation of expert estimates in the home matrix. Some authors suggest aggregating information using arithmetic and/or geometric averaging. On the other hand, the fuzzy Einstein WASPAS method has a clearly defined tool for aggregating expert preferences using a weighted Einstein averaging. This is important to emphasize, as some studies consider the impact of expert weights on the structure of aggregated information. Even though all the considered methodologies can be applied to process group decisions, the advantage is on the side of the fuzzy Einstein WASPAS methodology, due to a complete mathematical algorithm containing two functions for aggregation of expert preferences.

The Fuzzy Einstein WASPAS model defines weighting coefficients of criteria using a logarithmic additive function. The proposed methodology enables quick and easy defining relationships between ranked criteria and defining objective fuzzy weight criteria. This fuzzy Einstein WASPAS algorithm module represents a significant advantage over other fuzzy MCDM techniques, as it eliminates the need for additional application of objective and/or subjective methods to define criterion weights.

6. Discussion and Policy Implications of the Study

As of 2021, climate change is not simply a theoretical threat revealed by scientific research or simulations. We are experiencing challenges caused by human-induced climate change in almost every aspect of our lives. How to set the proper strategies to transform the existing policies to mitigate climate change has to be of the highest priority for the regulatory authorities at every level. Unfortunately, as the academic literature supports, the interest groups' preferences on different alternatives of climate actions in urban mobility planning may not be parallel to each other because of economic, political, or technical factors. Yet, the development and implementation of the projects require volunteered participation of all the stakeholders. Any kind of intervention or regulation should at least be acceptable to the public and businesses. In that respect, the small-scale, urban or regional mobility projects are sometimes easier to implement.

Here, we have used a case scenario to illustrate how the climate mitigation strategies in urban mobility planning can be chosen by taking different factors into account. These factors are related to the interests of society in different dimensions. In this regard, we surveyed experts from academia and business to construct a set of criteria that reflects the social dynamics among the public, business, and government. The results show that the highest-ranked alternative is the implementation of zero-emission zones. The second-ranked alternative becomes the central planning of the public/private transportation options, such as shuttles, personnel services, or taxicabs. The third-ranked alternative is micro-mobility. The results show that the environmental effects of alternatives are significantly taken into consideration. Also, the role of economic dimensions is considerably high. In that respect, implementing zero-emission zones is preferable, although it is costlier in all dimensions; politically, economically, and technically. The benefits derived from the environmental dimension dominate the costs. However, the second and third-ranked alternatives do not show the same pattern of choice. Although the micro-mobility-centered plans may offer stronger climate change solutions, the societal needs suppress the environmental benefits. Especially, inclusiveness and equity are important desired features for a climate project. Taking the aging society and the limited benefits that the elderly and the children can obtain from the micro-mobility, stronger support for centrally planned public transportation than the one for the micro-mobility prior mobility plans is understandable.

As Colebatch (2006) formalizes, in the policy-making process, the game evolves in terms of outcomes maybe even in terms of its rules. The expected or intended "effective" outcomes may not be implemented or even be chosen because of a political system or existing other societal dynamics. In the case of a sector where the positive and negative externalities are significantly high and where the stakeholders may have quite diversified interests, such as transportation, implementing a working policy that also has pre-specified ultimate goals like climate action is a complex issue. As the findings of our case scenario point out, an alternative that may not be environmentally or economically best can be inclusive so that it affects the approval decision of different groups of the society. The policy formation also changes the public opinion of the policymakers so that the next steps on the way of implementing more effective policies can be taken more safely.

We can state that in taking the climate action the societal needs are as important as the role of economic dynamics. The results emphasize the benefits of inclusive and equitable urban mobility plans. The best climate change solution plan is not always the economically or technically efficient one. The short-term preferences of the society should be balanced with long-term benefited climate actions and the needs of the society for inclusive and equitable solutions should be taken into consideration.

7. Conclusion

In our case, the best alternative among the three climate-change mitigating urban mobility plans appears to be the one that is most sustainable, inclusive, equitable but the costliest economically. Also, the second and third choices are ranked not upon their environmental effects. The study shows that economic and technical and financial constraints are important and the need for environmental actions is an absolute must. Yet, inclusiveness and support from different stakeholders are prior both in planning and implementation. In achieving the conclusion, the case scenario developed contributes to the literature in a way that it pools alternatives that are very good-looking on papers and that are practiced earlier. How the decision-makers take their choices affects the social dynamics. Thus, the benefits of the climate action urban mobility plans should be critically assessed regarding the societal dynamics.

Extending the results of our case scenario, we highly recommend the use of small-scale urban mobility plans that are environmental, inclusive, equitable, and technically efficient. The financial requirements are important. Yet, whenever the recent benefits are fair enough and funding is available, society will be ready to invest in future benefits. Therefore, the regulatory authority can find common support for big policy transformations from traditional ones to sustainable and environment-friendly ones even if the economic costs on the society are high.

In this study, we used expert opinions from a developing country to assess three practical small-scale urban mobility alternatives under a set of criteria that is constructed to represent the societal dynamics with economic, political, environmental, and technical dimensions. A higher number of small-scale urban mobility plans should be tested as a further study. The societal dynamics are not static and may change over time across the countries. A bigger survey for comparing the effects of different demographic, cultural, technological, or political features would be a strong contribution to the literature. The role of economic dynamics can be tested for different climate action plans for developing and developed countries separately.

The multi-criteria methodology presented in this paper belongs to the hybrid methods developed to fuse the advantages of several decision-making tools. Designing such hybrid procedures generates powerful tools for rational and objective decision-making. However, in addition to the benefits of the fuzzy Einstein WASPAS methodology shown, there are some limitations. One limitation is the impossibility of representing the mutual relations between the criteria. Therefore, it is necessary to direct further research towards implementing Bonferroni and Heronian functions in the Einstein WASPAS methodology. Applying Bonferroni and Heronian functions with Einstein norms would enable the presentation of interrelationships between criteria and would further enhance the flexibility of the Einstein WASPAS model. Therefore, a Fuzzy Einstein-based WASPAS decision support system should be developed. Thus, it will remove the limitations of the complexity of the mathematical model and become acceptable to more experts. Also, another limitation of this study is the lack of quantitative attributes in the home matrix. Therefore, the findings based on one case study cannot be generalized, but it is necessary to develop future research to provide quantitative information. In addition, further research should be directed towards applying other generalizations of the fuzzy theory are fuzzy Einstein WASPAS methodology, which would further objectify the process of processing subjectivity. Also, an exciting direction for further research is the implementation of hybrid fuzzy rough sets in the presented multi-criteria methodology.

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