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Article

Integrating fuzzy multicriteria decision making approach for improving the quality of urban mobility services in developing countries

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Abstract: In developing countries, urban mobility is a significant challenge due to convergence of population growth and the economic attraction of urban centers. This convergence of factors has resulted in an increase in the demand for transport services, affecting existing infrastructure and requiring the development of sustainable mobility solutions. In order to tackle this challenge, it is necessary to create optimal services that promote sustainable urban mobility. The main objective of this research is to develop and validate a comprehensive methodology framework for assessing and selecting the most sustainable and environmentally responsible urban mobility services for decision makers in developing countries. By integrating fuzzy multi-criteria decision-making techniques, the study aims to address the inherent complexity and uncertainty of urban mobility planning and provide a robust tool for optimizing transportation solutions for rapid urbanization. The proposed methodology combines three-dimensional fuzzy methods of type-1, including AHP, TOPSIS and PROMETHEE, using the Borda method to adapt subjectivity, uncertainty, and incomplete judgments. The results show the advantages of using integrated methods in the sustainable selection of urban mobility systems. A sensitivity analysis is also performed to validate the robustness of the model and to provide insights into the reliability and stability of the evaluation model. This study contributes to inform decision-making, improves policies and urban mobility infrastructure, promotes sustainable decisions, and meets the specific needs of developing countries.

Keywords: multi-criteria decision-making; sustainable urban mobility; developing countries; hybrid method; mobility service; sensitivity analysis

1. Introduction

According to projections from the United Nations, it is estimated that by 2050, approximately 70% of the global population will reside in urban areas (Samalna et al., 2023; Van Hoof and Marston, 2021). This demographic shift, coupled with the allure of economic opportunities, presents a significant challenge for urban mobility in these regions. This ongoing trend presents intricate challenges concerning urban mobility services, which significantly impact the quality of life for citizens and impede the economic, social, and environmental development of developing nations. Developing cities frequently grapple with issues such as congestion, pollution, road safety concerns, and limited access to public transportation. These problems arise from various factors, including inadequate transport infrastructure, underutilization of new technologies in transportation systems, and difficulties related to multimodal integration (Abdel and Abd, 2020; Mfenjou et al., 2018). In an attempt to enhance mobility, city managers in these countries sometimes resort to strategies such as constructing new roads and implementing cost-effective yet inefficient transportation services. In addition, the utilization of new technologies to support decision-making in the field of urban mobility is largely absent. Thus far, the measures taken have failed to provide sustainable solutions and adequately address the needs of urban inhabitants.

Furthermore, as urbanization continues to increase and travel demand rises, there is a growing necessity to enhance urban mobility services in order to foster the development of more sustainable, inclusive, and efficient cities. Achieving this goal requires an integrated approach that combines innovative technological solutions, strategic urban planning, and well-informed decision-making. Decision support tools, such as multicriteria decision analysis (MCDA) models are essential because they enable decision-makers to evaluate and prioritize multiple, often conflicting, criteria in complex decision scenarios. This is particularly important in urban mobility planning, where factors such as cost, environmental impact, social acceptance, and technical feasibility must be balanced (Kumar, 2020).

Fuzzy-based MCDM methods are especially valuable due to their ability to handle the inherent uncertainty and imprecision in human judgments and real-world data. These methods use fuzzy logic to quantify and manage uncertainty, allowing for more nuanced and flexible decision-making. By incorporating fuzzy logic, MCDM models can better accommodate the subjective and often vague nature of criteria assessments, leading to more accurate and reliable outcomes. This is particularly beneficial in the context of developing countries, where data may be incomplete or unreliable, and decision-making environments are often characterized by high levels of uncertainty and variability. Traditional decision-making approaches often struggle to account for the subjective, uncertain, and incomplete judgments inherent in such evaluations. In additional, some approaches have limitations, particularly in their ability to address complex interdependencies among criteria (Lin et al., 2020). Therefore, there is a pressing need for methodological frameworks that can effectively address the multifaceted nature of urban mobility decision-making in these contexts.

This paper presents a novel methodological approach that integrates fuzzy multicriteria decision making to assess and evaluate urban mobility services in developing countries. The proposed approach aims to provide decision-makers with a robust framework to systematically analyze and prioritize various mobility alternatives, considering sustainability factors and the specific context of developing countries. By incorporating fuzzy logic methods such as the analytic hierarchy process (AHP), technique for order of preference by similarity to ideal solution (TOPSIS), and preference ranking organization method for enrichment evaluation (PROMETHEE), the proposed approach offers a comprehensive and flexible decision-support system considering subjectivity and uncertainty. The inclusion of Borda method further to avoid result dependencies and enabling decision-makers to make informed and reliable choices. To address this issue, a set of objectives has been established:

- Provide a comprehensive review of multicriteria decision support methods in sustainable mobility;
- Develop a robust and flexible decision-making framework to evaluate policies and projects in sustainable mobility, considering the multiple dimensions and

specificities of developing countries;

- Conduct a sensitivity analysis to validate the robustness and stability of the evaluation model and provide insights into the reliability of the proposed approach.

This study provides a significant contribution to the field of urban mobility in developing countries by offering a comprehensive, adaptable, and reliable decision-making framework. The insights and impacts derived from this research have the potential to transform urban mobility planning, promoting more sustainable, efficient, and context-appropriate transportation solutions. The rest of the paper is structured as follows: Section 2 presents the state of the art concerning sustainable urban mobility and decision-making tools. In section 3, the methodology for integrating fuzzy decision support tools to enhance the quality of urban mobility services in developing countries is described, followed by the presentation of a case study in section 4. The final section concludes the work and provides directions for future research.

2. Literature review

In this section, the state-of-the-art related sustainable urban mobility system in general and particularly in the context of development country and decision-making methods are presented.

2.1. Sustainable urban mobility in developing countries

Mobility services refer to the range of transport solutions available to meet the travel needs of individuals and goods (Calderón and Miler, 2020). In developing countries, mobility services have evolved over time, transitioning from traditional modes of transportation to modern solutions. Initially, mobility services relied on traditional modes such as public transportation, taxis, and bicycles. These services were often characterized by limited infrastructure, inflexible schedules, and affordable costs (Samalna et al., 2023). However, they also had drawbacks such as overcrowding, traffic congestion, inefficiency, and uneven distribution of services (Ngossaha et al., 2024).

In recent decades, developing countries have witnessed the emergence of modern mobility services through the adoption of advanced technologies (Saxena and Gupta, 2020; Vij et al., 2020). These modern solutions include:

- On-demand transportation refers to a transportation system where users can book personalized travel services according to their specific needs. Unlike traditional public transportation with fixed schedules and predetermined routes, on-demand transportation allows users to request transport services to a specific location and time, usually through a mobile application or a call center. With companies such as Yango, Uber, and Bolt, on-demand transportation has become popular in countries such as Cameroon, South Africa, Kenya, Nigeria, Morocco, Egypt, China, and India. Citizens of these countries are willing to pay higher fares and wait longer to access a responsive on-demand transportation system (Anburuvel et al., 2022);
- Carpooling allows individuals to share a car ride, typically with people heading in the same direction (Abdelaziz and Nova, 2023). It is facilitated by platforms

like BlaBlaCar and Carpool Arabi and is also booming in certain developing countries such as Morocco, Rwanda, South Africa, Brazil, etc. Potential disadvantages of carpooling include dependence on driver availability and the need to coordinate schedules and routes;

- Bike and scooter sharing: Bike sharing provides users with access to shared bicycles for short trips;
- Multimodal transportation, which integrates different modes of transport such as buses, trains, bicycles, and carpooling services, is also being implemented in some developing countries to enhance the overall efficiency of the mobility system (Calderón and Miler, 2020);
- Mobility as a service (MaaS): MaaS is a concept that enables users to access various modes of transport (such as buses, trains, bicycles, etc.) through an integrated digital platform for sustainable system (Abassi et al., 2020). It is increasingly visible in numerous countries such as Cameroon, Morocco, India, etc.

Some countries have also embraced the concept of electric self-service vehicles to reduce greenhouse gas emissions (Ho and Tirachini, 2024). These services have introduced new benefits such as flexible schedules, diverse transportation options, more efficient resource utilization, and an enhanced user experience through features like real-time tracking and electronic payments, thereby improving accessibility and connectivity for local populations (Cipriano et al., 2021). This is sustainable mobility. Indeed, thanks to the contribution of technologies, sustainable mobility corresponds more generally to the response to the needs of users in relation to their daily activities (i.e., going to work, taking care of themselves, having fun, etc.), and considering considers the fact that these needs can be met without travel.

According to Canitez (2019) and Melkonyan et al. (2022), sustainable urban mobility is defined as a system that provides efficient access to goods and services, employment markets, and social connections while limiting negative short- and long-term consequences on environmental, social, and economic services. With the evolution of urban mobility policies, various cities, governments, and organizations have undertaken initiatives to shape the future of sustainable urban mobility in modern societies (Melkonyan et al., 2022). According to Magalhães and Santos (2022), it is necessary to introduce a new Sustainable Urban Mobility Plan. This plan entails reducing car usage, promoting active transportation modes, and suggesting measures such as urban traffic reduction, reallocating space in favor of public transport, and improving urban quality of life (Banister, 2008).

However, the transition from traditional services to modern solutions is not without challenges (Mubiru and Westerholt, 2024; Storme et al., 2021). Some disadvantages of traditional services persist, such as dependence on existing infrastructure, resistance to change, regulatory issues, and the inclusion of marginalized populations who may not have access to new technologies (Storme et al., 2021). In this context, it is essential to understand the causes and drawbacks of traditional mobility services in developing countries. By identifying these issues, it becomes possible to implement policies and measures aimed at improving mobility services and promoting the adoption of more efficient and sustainable modern solutions (Mubiru and Westerholt, 2024). Furthermore, it is important to seize the opportunities presented by these new technologies to address mobility challenges and enhance the quality of life for populations in developing countries. **Table 1** presents some new mobility services using new technology in developing countries.

Table 1. Key works on mobility services in developing countries.

Authors	Research problem	Mobility service
Hasselwander et al. (2022)	Examining the potential adoption of mobility as a service (MaaS) in developing countries	Public transportation, shared vehicles, active modes of transportation, on-demand transportation, sustainable transportation infrastructure
Calderón and Miler (2020)	Mobility as a service (MAAS) offering	Carpooling, bike-sharing, on-demand public transportation, ride-hailing
Anburuvel et al. (2022)	Analysis of public transportation demand in a developing country	Improved public transportation, carpooling, bike-sharing
Shaaban et al. (2021)	Intelligent transportation systems in a developing country: Benefits and implementation challenges	Intelligent transportation systems
Das et al. (2021)	Comparative evaluation of ridesharing solutions in India	Ridesharing
Cipriano et al. (2021)	Data-driven dynamic rebalancing for bike-sharing systems	Bike-sharing

Although these various works have made progress in sustainable mobility, most of them are still not applicable in some developing countries, particularly in Africa which are characterized by lack of infrastructure and poor management of information systems. This highlighted the need to develop services that considered the specific realities of these countries.

2.2. MCDM methods and sustainable urban mobility services

In the field of research on sustainable urban mobility in developing countries, numerous authors have made significant contributions in identifying issues and proposing solutions. For instance, Ngossaha et al. (2024) emphasized the importance of reducing air pollution, fostering collaboration among stakeholders, and integrating mobility services to enhance sustainability. Anburuvel et al. (2022) conducted an analysis on transport demand in developing countries. According to their findings, improving public transportation in developing countries necessitates considering factors such as service quality, accessibility, passenger information, and socioeconomic aspects. They also recommended the implementation of robust institutional policies, stakeholder integration, the utilization of advanced technologies, and coordination across different modes of transportation to optimize available resources and provide efficient and tailored transport solutions that meet the population’s needs. Demissie et al. presented a methodology for estimating passenger demand for public transport services using mobile phone data. Vij et al. (2020) examined consumer demand and willingness to pay for on-demand transport services. Shaaban et al. (2021) discussed the experience and challenges associated with implementing intelligent transportation systems in some developing countries.

Various types of operations research methods have been developed to assist decision-makers in evaluating mobility services. Among them, multiple-criteria decision-making (MCDM) helps decision-makers rank or sort different alternatives based on multiple often conflicting criteria (Huang et al., 2021). MCDM has become increasingly popular in sustainable mobility in recent years as it allows for the consideration of different types of criteria (not just environmental criteria) (Huang et al., 2021). A study conducted by Broniewicz and Ogrodnik (2021) identified 52 indexed articles in the Scopus and Web of Science databases using the keywords "MCDM/MCDA in transport" and published between 2020 and 2021. During this analysis, more than 25 different MCDM methods were identified. Additionally, a search conducted by us using the keyword "MCDM + Sustainable urban mobility" in the Google Scholar database yielded 32 relevant articles published between 2021 and 2023. Among these articles, 15 used hybrid methods, while 13 used traditional MCDM methods. From both studies, it can be concluded that the most commonly used methods are AHP, PROMETHEE, TOPSIS, ViKOR, and DEMATEL (Broniewicz and Ogrodnik, 2021; Sharma, 2018).

This analysis highlights the most commonly used methods in the scientific literature for addressing multicriteria decision-making issues in the context of sustainable mobility. **Figure 1** presents the most used MCDM methods in the field of sustainable mobility between 2021 and February 2024.

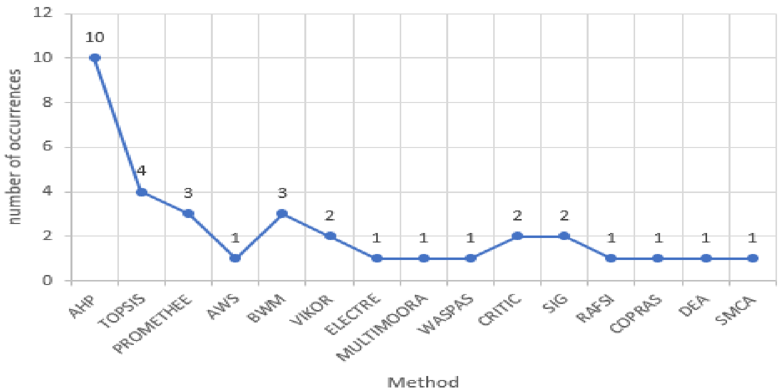

Figure 1. The most commonly used MCDM methods in the field of sustainable mobility between 2021 and February 2024.

The following **Table 2** presents the compilation of MCDM methods applied to sustainable urban mobility services in developing countries published in google scholar, highlighting the research question and the corresponding MCDM method used. The various articles listed contribute to the creation of the **Figure 1**.

Table 2. Compilation of literature review pertaining to multi-criteria methods applied into sustainable urban mobility services in developing countries.

Authors	Research question	MCDM method	Location
Safety and quality of public transportation			
Verma and Rastogi (2024)	Evaluation of the quality of public transportation services from stakeholders' perspective	Fuzzy AHP	LDC
Trivedi et al. (2024)	Evaluating and prioritizing road safety improvements	AWS and TOPSIS	India
Imtiyaz et al. (2023)	Prioritizing for improving public transportation services	AHP	LDC
Shojarazavi et al. (2023)	Role of intelligent transportation in urban planning and transition towards smart cities in developing countries with sustainability requirements	AHP	Iran

Table 2. (*Continued*).

Authors	Research question	MCDM method	Location
Safety and quality of public transportation			
Solanki et al. (2024)	Optimizing operational parameters based on operators and users affecting urban public transport system	AHP, GP	LDC
Zehmed et al. (2020)	Measuring and evaluating bus service quality at urban route level	Fuzzy SERVPERF, DEA	Morocco
Kumar (2020)	Importance of social sustainability indicators in the freight transport industry	Fuzzy BWM	India
Development of public transportation systems			
Moslem (2024)	Sustainable and efficient solutions for improving bus public transportation system	P-SF-AHP	India
Gokasar et al. (2023)	Identification and proposal of alternatives for incident management on highways using autonomous vehicles in mixed traffic	T2NN-COPRAS	LDC
Bouraima et al. (2023)	Identification of key challenges in implementing and successfully operating a high-level bus rapid transit system	Weighted ratio analysis	Tanzania
Demir et al. (2023)	Evaluation of railway transport systems	Fuzzy AHP, Fuzzy VIKOR	Turkey
Lungu et al. (2023)	Prioritization of road maintenance or rehabilitation	Review-based	LDC
Mesa et al. (2023)	Classification and selection of policy measure options for sustainable urban development of land use and transportation	AHP, TOPSIS	Thailand
Bhuiya et al. (2023)	Selection of bus stop locations for line 3 of the bus rapid transit system	AHP	Bangladesh
Ibrahim et al. (2023)	Identification and prioritization of potential areas for transit-oriented development	GIS, AMCS	Egypt
Yucesan et al. (2024)	Evaluation of urban mobility sustainability using the Sustainable Urban Transport Index	BWM, MULTIMOORA	LDC
Kundu et al. (2023)	Evaluation and selection of an appropriate urban transport system	Fuzzy BWM, MAIRCIA	
Carsharing and ridesharing			
Turoń (2022)	Vehicle selection for carsharing services	ELECTRE III	Poland
Abdel and Abd (2020)	Choice of a ridesharing station	WASPAS	LDC
Lin et al. (2020)	MULTIMOORA-based ADMC model for ridesharing station site selection	MULTIMOORA	China
Deveci et al. (2018)	Ridesharing station selection	WASPAS and TOPSIS	Turkey
Investment location choice			
Hezam et al. (2023)	Evaluation framework for sustainable transport investment projects	SVN, COPRAS, TOPSIS	LDC
Chowdhury and Haque (2023)	Identification of the best location for a new dry port	Fuzzy AHP, BWM, PROMETHEE	Bangladesh
Yagmahan and Yılmaz (2023)	Evaluating different possible locations for electric vehicle charging stations	AHP, TOPSIS, MOORA	Turkey
Keleş and Pekkaya (2023)	Evaluation of logistics center location choices	CRITIC, PROMETHEE	Turkey
Ibrahim et al. (2023)	Identification and prioritization of potential areas for transit-oriented development	GIS, SMCA	Egypt
Electric vehicles			
Tillu et al. (2024)	Integrated MCDM analysis of fuel and propulsion alternatives	AHP, ANP, TOPSIS, WSM, and VIKOR	India
Khan et al. (2024)	Sustainable design of charging stations for electric vehicles		Pakistan
Gokasar et al. (2023)	Implementation of electric vehicles in developing countries	RAFSI	LDC
Kaya et al. (2020)	Optimal planning of electric vehicle charging stations	AHP, PROMETHEE, VIKOR, GIS	Turkey

By examining the table of MCDM methods applied to urban mobility services in developing countries (**Table 2**), it is evident that various authors have utilized different techniques to address a range of issues related to public transportation, transport system development, car-sharing and ride-sharing, investment location choice, and electric vehicles. Among these methods, the analytic hierarchy process (AHP) is widely employed, underscoring its effectiveness in multi-criteria decision-making. However, it also reveals a problem with traditional methods: evaluations by exact numbers are not sufficiently adequate to express the nuanced thoughts and opinions of human experts. In other words, the classical method cannot appropriately capture the imprecision and ambiguity inherent in expert judgments. To address these shortcomings, mathematical frameworks such as fuzzy sets, soft sets, rough sets, and combinations thereof have been utilized (Sivaprakasam and Angamuthu, 2022). Among these, the fuzzy set theory proposed by Zadeh presents quite useful tools. Liu et al. (2020) have presented the different types of fuzzy sets as well as a comparative study between them. These include: type-1 fuzzy sets, type-2 fuzzy sets, intuitionistic fuzzy sets, and fuzzy scales. In the major work in question, the choice was made for type-1 fuzzy sets with a triangular representation, which appears to be best suited for the judgment of experts.

The application of fuzzy sets is crucial in decision-making and data analysis, as it enables the representation and management of uncertainty, imprecision, and subjectivity inherent in many real-world scenarios. By extending classical sets to allow for progressive degrees of membership, fuzzy sets provide a more flexible and realistic approach to modeling complex phenomena. The key advantages of fuzzy sets lie in their ability to handle information that traditional numerical data cannot, including: uncertainty and fuzziness, subjective judgments, complexity and ambiguity, and non-binary evaluations. Overall, fuzzy sets facilitate more realistic and nuanced representations of complex phenomena, thereby promoting more informed decision-making, particularly in contexts where precise numerical data is unavailable or insufficient, such as in developing countries.

In the literature, many authors have also employed hybrid approaches by combining different methods (Bouraima et al., 2023; Zehmed and Jawab, 2020) to obtain more comprehensive and reliable results. For example, the integration of AHP with other methods such as TOPSIS, PROMETHEE, or GIS enables the consideration of diverse aspects and criteria in a more exhaustive manner. These hybrid approaches allow decision-makers to gain a more nuanced understanding of the complex issues related to urban mobility in developing countries, thereby facilitating informed decision-making for the improvement of transportation services. A comparative study of some of the most commonly used methods is proposed in the following sections.

2.3. MCDM comparative study

The determination of the choice of MCDM for solving decision support problems such as urban mobility depends on several parameters such as the choice of evaluation criteria and the assignment of their respective weights. The determination of the criteria weights, for example, is an important step in MCDM models. The problem of weighting the criteria can have a significant influence on the final result of the decision-making process (Pamučar et al., 2018). It is therefore essential to use well-suited MCDM methods for this task. In the literature, several traditional methods have commonly been used to determine the weights of the criteria, such as AHP, the BWM method, the SMART method, or the DEMATEL method. However, these methods have advantages and disadvantages (Roberts and Goodwin, 2002). Among these methods, AHP is the most widely used as shown in **Figure 1** due to its many advantages, notably: the representation of the problem in the form of a hierarchical structure, the calculation of the consistency ratio which proves the consistency in the judgment of the experts, and a complexity adapted for a small number of criteria, hence its choice for our Moskolai et al. (2017) model.

Among the alternative methods to AHP, we have studied some new approaches in the literature, such as FUCOM, LBWA and OPA. Although these methods have many advantages, AHP has proven to be the best choice for our complex hierarchical decision problem. The FUCOM (full consistency method) method present by Pamučar et al. (2018) has the main advantages of a significantly lower number of comparisons ($n - 2$) compared to $n(n - 1)/2$ for AHP, a consistent comparison of the criteria, and the calculation of reliable values of the criteria weighting coefficients, which contribute to a rational judgment. However, FUCOM does not allow as fine a modeling of the interdependencies between criteria as the hierarchical structure of AHP. The LBWA (level based weight assessment) method developed by Žižović and Pamucar (2019) has 4 main advantages: a small number of comparisons ($n - 1$), adaptability to complex situations, a simple mathematical method for calculating weights, and the integration of a sensitivity analysis. Although this approach is interesting for determining the weights of the criteria, it does not benefit from a solid theoretical framework and as much application experience as AHP. As for the OPA (optimal priority assessment) method proposed by Ataei et al. (2020), it aims to determine the optimal weights of the criteria based on a mathematical optimization model. Although promising, this method is still relatively unproven compared to AHP, which benefits from a broad consensus in the MCDM literature.

Over the past ten years, numerous methods have emerged that offer many advantages, such as: multi-attribute ideal-real comparative analysis (MAIRCA) introduced in 2014 by Pamucar et al. (2014). Its main advantages are that it can be used for problems with many criteria and alternatives, it can handle both qualitative and quantitative criteria, and it is easy to understand and apply. Measurement of alternatives and ranking according to compromise solution (MARCOS) proposed in 2020 by Stević et al. (2020). It is based on defining the relationship between the alternatives and the reference values (ideal and anti-ideal solutions). Its advantages include considering an anti-ideal solution, more accurate determination of the degree of utility, and the ability to handle a wide range of criteria and alternatives. Another method is multi-attributive border approximation area comparison (MABAC) developed in 2015 by Pamučar and Ćirović (2015). Unlike other MCDM methods, it is based on calculating the distances of each alternative criterion function to the proximity area of the border. It is a compensation method where the attributes are not linked to each other, and qualitative attributes are transformed into quantitative ones.

While these new methods offer interesting advantages, they are relatively new and have not yet been as widely used and validated as AHP, TOPSIS, and

PROMETHEE. Furthermore, TOPSIS and PROMETHEE are well-established methods, with many successful applications in various fields. Their maturity, flexibility, and ability to effectively handle multi-criteria decision-making problems make them good choices for many applications. Their age (developed in the 1980s) is also an asset in terms of reliability and validation (see **Table 2**). However, they also have some drawbacks that could be compensated for in a hybrid method, as presented in our proposed hierarchy. **Table 3** presents a comparative study of the most used methods.

Table 3. Synthesis of comparative MCDM.

Criteria for comparison	AHP	TOPSIS	PROMETHEE
Methodology	Hierarchical structure of the problem for pairwise comparison hierarchical structure of the problem for pairwise comparison	Calculation of the distance to positive ideal solution and negative ideal solution	Calculation of positive outranking flow and negative outranking flow
Nature of attributes	Quantitative and qualitative	Quantitative	Quantitative and qualitative
Necessity to understand the importance of criteria	Yes	Yes	Yes
Methods for determining the weights of criteria	Calculated	No	No

The **Table 3** presented the advantages and disadvantages of each of the traditional MCDM methods. Combining them should allow to compensate for the shortcomings of individual approaches and to take advantage of the benefits of each one, while also eliminating the dependence of the results on a single method for the evaluation of urban mobility criteria in developing countries.

2.4. Main goal and positioning

Despite the numerous studies on the use of fuzzy multicriteria approaches for the evaluation and improvement of urban mobility services, there is still a lack of research specifically focusing on the application of these methods in the context of developing countries. The unique challenges faced by these countries, such as limited resources, inadequate infrastructures of mobility systems, require adapted solutions that consider local priorities and constraints. It is therefore essential to explore how fuzzy multicriteria decision-making approaches can be specifically designed and implemented to address these challenges in the context of sustainable urban mobility in developing countries. The main goal of this study is to develop and validate a comprehensive fuzzy-based multi-criteria decision-making framework for assessing and selecting sustainable urban mobility services in developing countries. Positioned at the intersection of urban planning, sustainable development, and decision science, this research addresses critical gaps by providing a flexible and nuanced approach to decision-making that can handle the inherent complexity and uncertainty of urban mobility planning. The framework integrates advanced decision support tools such as AHP, TOPSIS, PROMETHEE, and the Borda method, offering a holistic evaluation of multiple criteria including cost, environmental impact, and social acceptance. The study aims to support policymakers and urban planners in making well-informed, sustainable, and context-appropriate transportation decisions.

3. Proposed methodological framework

In this study, aiming to propose integrated fuzzy hybrid multicriteria decision-making method for improving sustainable urban mobility in developing countries, our approach follows the steps presented in **Figure 2**. This methodology consists of several steps that allow for defining the decision problem, selecting experts, determining criteria and sub-criteria, evaluating their importance, ranking alternatives, and providing a final ranking based on the majority rule, as illustrated in **Figure 2**.

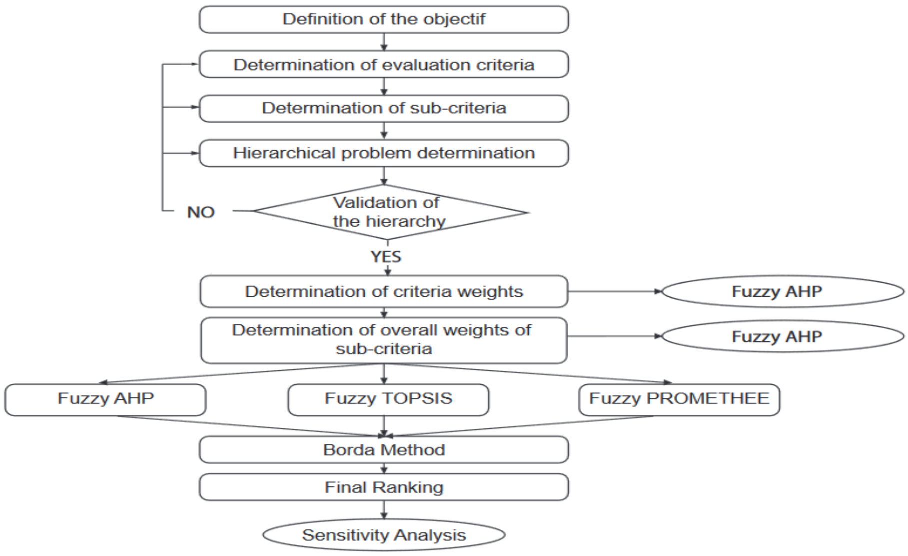

Figure 2. Proposed methodology.

Step 1: Definition of the decision problem

The first step is to define the decision problem. This step is crucial to clarify the objectives, constraints, and challenges related to the evaluation of sustainable urban mobility services in developing countries. It requires a thorough analysis of the stakeholders' needs and specific mobility issues.

Step 2: Selection of experts

The second step involves selecting the experts who will participate in the evaluation of sustainable urban mobility services. This is very important step to ensure the relevance and quality of the assessments. The selected experts must possess expertise in key areas such as urban planning, transportation, environment and economics. Their experience and knowledge will bring diverse and complementary perspectives during the evaluation of criteria and alternatives. In this study, a group of three experts consisting of an urban planner, an economist and an environmentalist were consulted.

Step 3: Selection of criteria

The third step of the methodology involves selecting the evaluation criteria for improving the quality of sustainable urban mobility services. This step is essential as it determines the key aspects to be considered when evaluating alternatives. The criteria can be multiple and varied, including social, environmental, economic, technical, etc. The selection of criteria is generally based on project objectives, stakeholder needs, and specific constraints related to the context of developing countries. It is important to choose relevant, measurable, and meaningful criteria that will enable a holistic evaluation of sustainable urban mobility services. This step may also involve consulting the selected experts to gather their opinions and recommendations on the criteria to be included. In the previous work of Ngossaha et al. (2017), criteria and sub-criteria for evaluating sustainable mobility services based on knowledge elicitation and a thorough literature review is proposed. Many other authors, such as Curiel-Esparza et al. (2016) and Zapolskyte et al. (2022), have relied on literature review to determine criteria and sub-criteria. Once the criteria are selected, they will serve as the basis for evaluating alternatives in the subsequent steps of the methodology.

Step 4: Selection of sub-criteria

The fourth step of the methodology involves selecting sub-criteria for the evaluation of sustainable urban mobility services. Sub-criteria are specific elements that contribute to the measurement and evaluation of the previously defined main criteria. They help break down the criteria into more detailed and specific elements, providing a better understanding of the different dimensions to consider when evaluating alternatives. The sub-criteria may vary depending on the selected criteria. They will serve as the basis for the detailed evaluation of alternatives in the later steps of the methodology.

Step 5: Hierarchical structure

The fifth step of the methodology involves structuring the criteria and sub-criteria hierarchically. This step aims to organize the criteria and sub-criteria into a logical and hierarchical structure, enabling a better understanding of the relationships and inter-dependencies among them. If the initial hierarchical structure is not satisfactory, i.e., if it does not align with the objectives and relationships between criteria and sub-criteria, it is necessary to revisit the previous steps, including the selection of experts, criteria, and sub-criteria, to adjust and align them properly. Once the hierarchical structure is validated, meaning it aligns with the objectives and relationships among the elements, the subsequent steps of the methodology can be pursued.

Step 6: Determining weights

The next step in the methodology, after validating the hierarchical structure, is determining the weights of the criteria using fuzzy AHP. The implementation is given in steps 7.

The determination of sub-criteria weights follows, using a similar approach to the one used for criteria. Experts assess the sub-criteria in relation to their relative importance within each criterion. The weights of the sub-criteria are calculated using fuzzy AHP, considering the evaluations of the experts and the hierarchical structure established earlier.

Step 7: Ranking of alternatives

The next step of the methodology involves ranking the alternatives. This step aims to evaluate and rank the different alternatives of sustainable urban mobility services based on the established criteria and sub-criteria. Three distinct methods are used in this step: fuzzy AHP, fuzzy TOPSIS, and fuzzy PROMETHEE.

1) Fuzzy AHP (analytic hierarchy process) is used to evaluate the alternatives with respect to the criteria and assign fuzzy values representing the degree of performance of each alternative on each criterion. The previously determined

criteria weights are considered to aggregate these fuzzy values and obtain an overall evaluation of each alternative. The method is described in five stages:

Stage 1: Construction of the expert evaluation matrix. For each expert, construct an $n \times n$ pairwise comparison matrix of the criteria by their triangular fuzzy scales as presented in **Table 4**, as shown in the following matrix: $\tilde{C}_i = \begin{pmatrix} 1 & \cdots & \tilde{x}_{1n} \\ \vdots & \ddots & \vdots \\ \tilde{x}_{n1} & \cdots & 1 \end{pmatrix}$, with:

$$\tilde{x}_{ij} = \begin{cases} \left(\frac{1}{l_i}, \frac{1}{m_i}, \frac{1}{h_i}\right), \text{for } \forall i < j \\ (1, 1, 1), \text{for } \forall i = j \\ (l_i, m_i, h_i), \text{for } \forall i > j \end{cases} \tag{1}$$

Table 4. Saaty's fuzzy weight.

Linguistic	**Scale of fuzzy number**
Equal	(1, 1, 1)
Weak advantage	(1, 2, 3)
Not bad	(2, 3, 4)
Preferable	(3, 4, 5)
Good	(4, 5, 6)
Faily good	(5, 6, 7)
Very good	(6, 7, 8)
Absolute	(7, 8, 9)
Perfect	(8, 9, 10)

Stage 2: Aggregation of expert judgements. The different expert matrices are aggregated using the:

$$\widetilde{C_{ij}} = (l_{ij}, m_{ij}, h_{ij}) = \left(\prod_{t=1}^{q} \widetilde{C_{ij}}^{(t)}\right)^{\frac{1}{q}} = \widetilde{C_{ij}}^{(1)} \otimes \widetilde{C_{ij}}^{(2)} \otimes \ldots \otimes \widetilde{C_{ij}}^{(q)} \\ = \left(\prod_{t=1}^{q} l_{ij}{}^{(t)}, \prod_{t=1}^{q} m_{ij}{}^{(t)}, \prod_{t=1}^{q} h_{ij}{}^{(t)}\right) \tag{2}$$

Stage 3: Consistency of judgement. The consistency ration (CR) is calculated using the formula:

$$CR = \frac{CI}{RI}, \text{with } CI = (\lambda_{\max} - n)/(n-1) \tag{3}$$

where n is the size of the matrix and $\lambda_{\max}$ is the maximum eigenvalue for assessing the consistency of the experts' judgements. It helps to measure the degree of consistency of the assessments made by the experts in the overall comparison matrix. If the CR is less than 0.1, this indicates acceptable consistency of judgements. Otherwise, the experts' judgements need to be reviewed and adjusted. The RI index for matrices of size 1 to 10 are proposed in (Saaty, 2008).

Stage 4: Determining fuzzy weights. The geometric mean is used to synthesise different perspectives and also an approximation of the eigenvalues of a matrix.

$$\tilde{C}_i = \left(\tilde{C}_{i1} \oplus \tilde{C}_{i2} \oplus \ldots \oplus \tilde{C}_{in}\right)^{1/n} \tag{4}$$

$$\tilde{W}_i = \frac{\tilde{C}_i}{\sum_{j=1}^{n} \tilde{C}_j}$$

Stage 5: Defuzzification of the fuzzy weights. The fuzzy weights obtained are then defuzzified to obtain real weights using the formula:

$$x^* = \frac{l + m + h}{3} \tag{5}$$

2) Fuzzy TOPSIS is a method that compares the alternatives to an ideal solution and an anti-ideal solution. Distances between each alternative and these solutions are calculated using the fuzzy values of the criteria. The alternative that is closest to the ideal solution and furthest from the anti-ideal solution is considered the best. The steps involved in implementing fuzzy AHP can be summarized as follows:

Let's say, the decision group has k members and the i-th alternative on j-th criterion. The fuzzy rating and importance weight of the k-th decision maker, about the i-th alternative on j-th criterion.

Stage 1: Construction of the expert comparison matrix using the fuzzy linguistic variable or number (see **Table 5**):

Table 5. Fuzzy ratings for linguistic variables of TOPSIS.

Linguistic variable	**TFN**
Very poor (VP)	(1, 1, 3)
Poor (P)	(1, 3, 5)
Fair (F)	(3, 5, 7)
Good (G)	(5, 7, 9)
Very good (VG)	(7, 9, 10)

Stage 2: Aggregation of expert matrices

$$\tilde{x}_{ij} = (l_{ij}, m_{ij}, h_{ij})$$

where $\tilde{x}_{ij}$ is the aggregation comparison of criterion i relative to criterion j by differents experts, (l_{ij}, m_{ij}, h_{ij}) the corresponding fuzzy value.

$$l_{ij} = \min_k\{l^k{}_{ij}\}, m_{ij} = \frac{1}{k}\sum_k m^k{}_{ij}, h_{ij} = \max_k\{h^k{}_{ij}\} \tag{6}$$

Stage 3: Normalization of the expert matrix

Normalize the decision matrix $X = (x_{ij})_{m\times n}$ using the equation below.

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{n} x^2{}_{ij}}}, i = 1, 2, \dots, m; j = 1, 2, \dots, n \tag{7}$$

where r_{ij} is normalized value.

Stage 4: Calculate the weighted normalized decision matrix

$V = (v_{ij})_{m\times n}$ with

$$v_{ij} = w_j r_{ij}, i = 1, 2, \dots, m; j = 1, 2, \dots, n \tag{8}$$

where w_j is the relative weight of the j-th criterion, and $\sqrt{\sum_{j=1}^{n} w_j} = 1$.

Stage 5. Determine the positive ideal solution (PIS) and negative ideal solution (NIS)

$$A^{+} = \{v^{+}{}_{1}, \ldots, v^{+}{}_{m}\} = \left\{\left(\max_{j} v_{ij} \,/ j \in \Omega_b\right), \left(\min_{j} v_{ij} \,/ j \in \Omega_c\right)\right\} \quad (9)$$

$$A^{-} = \{v^{-}{}_{1}, \ldots, v^{-}{}_{m}\} = \left\{\left(\max_{j} v_{ij} \,/ j \in \Omega_b\right), \left(\min_{j} v_{ij} \,/ j \in \Omega_c\right)\right\} \quad (10)$$

With Ω_b and Ω_c being the set of benefit criteria and non-benefit criteria respectively give in the hierarchy structure.

Stage 6. The separation distance of the alternatives from the positive ideal solution and negative ideal solution is estimated.

$$D^{+}{}_{i} = \text{DFPIS} = \sqrt{\sum_{j=1}^{n} (v_{ij} - v^{+})^2}, i = 1, 2, \ldots, m \quad (11)$$

$$D^{-}{}_{i} = \text{DFPNIS} = \sqrt{\sum_{j=1}^{n} (v_{ij} - v^{-})^2}, i = 1, 2, \ldots, m \quad (12)$$

Stage 7. The comparative proximity of each alternative to the ideal solution is estimated. The relative closeness of the alternative A_i to the ideal solution A^* is defined as follows:

$$CC_i = \frac{D^{-}{}_{i}}{D^{-}{}_{i} + D^{+}{}_{i}} \quad (13)$$

Which allows to classify the different alternatives.

3) Fuzzy PROMETHEE is a method that compares the alternatives pairwise in terms of preferences. Fuzzy values of the criteria are used to determine the preferences of the experts. Fuzzy PROMETHEE generates a ranking of the alternatives based on the experts' preferences. The steps involved in implementing fuzzy AHP can be summarized as follows:

Stage 1: Construction of the fuzzy decision matrix.

In a situation where m alternatives and n criteria are presented to k decision-makers ($D1$, $D2$, ..., Dk) to choose the best alternative, a fuzzy MCDM problem can be expressed in the form of a matrix as shown below:

$$\tilde{C}_i = \begin{pmatrix} \tilde{x}_{11} & \cdots & \tilde{x}_{1n} \\ \vdots & \ddots & \vdots \\ \tilde{x}_{m1} & \cdots & \tilde{x}_{mn} \end{pmatrix}, i = 1, 2, \ldots, m; j = 1, 2, \ldots, n \quad (14)$$

where $\tilde{x}_{ij}$ represents the score assigned to alternative A_i with respect to criteria C_j, expressed in triangular fuzzy numbers (TFN). The notation of a decision-maker k is $\tilde{x}_{ij} = (l^{k}{}_{ij}, m^{k}{}_{ij}, h^{k}{}_{ij})$.

Stage 2: Aggregation of decision

In this step, the fuzzy weights of the criteria as well as the evaluations of the alternatives are aggregated using the formula:

$$\tilde{x}_{ij} = \frac{1}{n}\left[\tilde{x}_{ij}{}^{1} + \tilde{x}_{ij}{}^{2} + \cdots + \tilde{x}_{ij}{}^{n}\right] \quad (15)$$

Stage 3: Normalization of the decision matrix

The next step is to normalize the aggregated fuzzy decision matrix obtained in stage 2. The normalized fuzzy decision matrix is defined as: $\tilde{S} = \left[\tilde{s}_{ij}\right]_{m \times n}, i = 1, 2, \ldots, m; j = 1, 2, \ldots, n$ with

$$\tilde{s}_{ij} = \left(\frac{\tilde{l}_{ij}}{h_j^+}, \frac{\widetilde{m}_{ij}}{h_j^+}, \frac{\tilde{h}_{ij}}{h_j^+}\right) h_j^+ \quad (16)$$

Stage 4: Construction of the fuzzy preference function

In this step, the preference function

$$\tilde{P}_j(m,n) = \begin{cases} 0, \tilde{s}_{mj} \leq \tilde{s}_{nj} \\ 1, \tilde{s}_{mj} \geq \tilde{s}_{nj} \end{cases}, j = 1,2,\ldots,k \text{ for } j = 1, 2, ..., k \quad (17)$$

is calculated to describe the decision-makers' preference between pairs of alternatives.

Brans and Vincke introduced six types of preference functions ranging between [0, 1]. In this document, we have used the usual criterion function (type I) which is very simple to implement and allows obtaining the necessary results.

Stage 5: Calculation of the weighted aggregated preference function

The next step is to calculate the weighted aggregated preference function using the equation $\tilde{\pi}(m,l) = \sum_{j=1}^{k} \tilde{P}_j(m,n)\widetilde{w}_j$ where $\widetilde{w}_j$ is the relative weight of the criterion.

Stage 6: Calculation of the entering flow, leaving flow, and net flow

- Entering flow

$$\text{Flow+} = \widetilde{\emptyset}^+(m) = \frac{1}{n-1}\sum_{m \neq l} \tilde{\pi}(m,l), \forall m, l \in A \quad (18)$$

- Leaving flow

$$\text{Flow−} = \widetilde{\emptyset}^-(m) = \frac{1}{n-1}\sum_{m \neq l} \tilde{\pi}(l,m), \forall m, l \in A \quad (19)$$

- Net flow

$$\text{Net Flow} = \widetilde{\emptyset} = \widetilde{\emptyset}^+(m) - \widetilde{\emptyset}^-(m), \forall m \in A \quad (20)$$

Once the individual rankings are obtained for each evaluation method, the results are aggregated using the Borda method to derive a final ranking of the alternatives. The Borda method is a well-established voting technique utilized to consolidate individual preferences within a group decision-making context (Barak and Mokfi, 2019; Hafezalkotob et al., 2019). This approach assigns points to each choice based on its relative ranking in each individual preference, and then sums the points to determine the final ranking. This aggregation process helps to identify the best-performing alternatives based on the evaluated criteria and sub-criteria. The ranking step is essential for informed decision-making, as it provides a comparative evaluation of the alternatives and highlights those that best satisfy the defined objectives and criteria. By employing the Borda method, the analysis leverages the collective wisdom of the expert inputs to derive a comprehensive and robust ranking of the alternatives, which can then inform the ultimate decision-making process.

Step 8: Sensitivity analysis

The last step involves conducting a sensitivity analysis to justify the robustness of the proposed hybrid method. It aims to examine how much the sequence obtained by our hybrid method can vary with small changes in criterion weights.

Sensitivity analysis has been used by many authors to justify the robustness of the final ranking obtained. Maletivc et al. (2014) increased the weights of the main criteria by 25% compared to their initial values. The objective was to determine if the final results of the maintenance policy selection remained stable despite this increase in weights. Dogan (2021) performed a sensitivity analysis to show how changes in criterion weights can influence the ranking of alternatives. They modified each criterion weight from 0 to 1, increasing it by 0.1 each time, and new scores were calculated for each alternative. Demirc et al. (2022) used four approaches to verify the analysis results. First, the criterion weights were modified to see if there was a difference in the ranking. Then, the bottom alternatives were eliminated, and a sensitivity analysis was conducted based on the difference in the order-inversion function. Next, a comparative analysis was performed with other multi-criteria decision-making methods. Finally, the correlation coefficient was calculated based on the obtained rankings, and a model reliability analysis was conducted. For Ding et al. (2021), the values of the overall weights of each criterion, which illustrate the overall importance of that main criterion, as well as the value of the local weight, which illustrates the local importance within the main criterion, would be exchanged mutually between 2 criteria, while the values of the other criteria remain unchanged in the sensitivity analysis.

4. Case study

In order to validate the proposed model and analyze the feasibility of its application in a real problem, a case study was carried out. The case study is briefly described in the following section and it's based on the sustainability indicators according to Ngossaha et al. (2017) in their previous study.

4.1. Study context

The case study addresses a real-world problem related to urbanization and the development of a city. The city council of a developing country, whose name we will keep anonymous for confidentiality purposes, was planning to launch new urban projects aimed at improving traffic flow. The main challenge was to determine the target policy among five alternatives that aimed to improve transportation in the city and its surroundings: Policy 1 (development of an administrative zone), policy 2 (development of a commercial zone), policy 3 (development of an industrial zone), policy 4 (construction of a recreational area), policy 5 (construction of a bicycle lane in a shopping center). It should be noted that these policies were defined based on the needs of the city's citizens in various services, and transportation issues, in terms of infrastructure and facilities development, are implied. The interest of each project for the different stakeholders is given as follows:

- Development of an administrative zone: Consolidating administrative institutions and public services in one location reduces the need for travel to access them, thereby decreasing road traffic and carbon emissions.
- Development of a commercial zone: Creating shopping centers near residential areas reduces long-distance travel for shopping, thus promoting sustainable modes of transportation such as walking or cycling.
- Development of an industrial zone: Concentrating industrial activities in specific zones reduces transportation distances for goods, encouraging the use of more efficient modes of transportation and reducing road congestion.
- Construction of a recreational area: Building recreational spaces that are

accessible by walking or cycling promotes active transportation, reducing reliance on motor vehicles and promoting a healthy and sustainable lifestyle.

- Construction of a bicycle lane in a shopping center: Creating a bicycle lane in a shopping center encourages the use of cycling as a means of transportation for daily commutes and errands, thus reducing road congestion, carbon emissions, and promoting an active lifestyle.

The second step of the proposed methodology is the selection of experts/decision-makers who will evaluate the different criteria, sub-criteria, and alternatives in order to obtain the best ranking of the different alternatives. The panel of decision-makers consisted of two employees from different administrative domains of the council with over 10 years of experience, and a research professor with numerous publications in the field of sustainable mobility in developing countries. The goal of the work was to provide the council with decision support in choosing the best policy based on sustainability requirements. A survey (the associated form is not described here for anonymity) was submitted to the decision-makers, consisting of questions related to the mobility criteria identified in the following section. Each expert was asked to respond to the forms using a judgment matrix based on well-defined judgment values.

4.2. Results of the multi-criteria evaluation

4.2.1. Criteria and sub-criteria selection

The concept of sustainable mobility is designed to address urban problems related to traffic, congestion, air pollution, noise, and to make urban mobility more convenient and attractive for every citizen. Maintaining a sustainable mobility system in cities is a rather complex process, achieved by integrating various measures. The objective of this step is to select detailed indicators that will be used to assess the level of mobility sustainability.

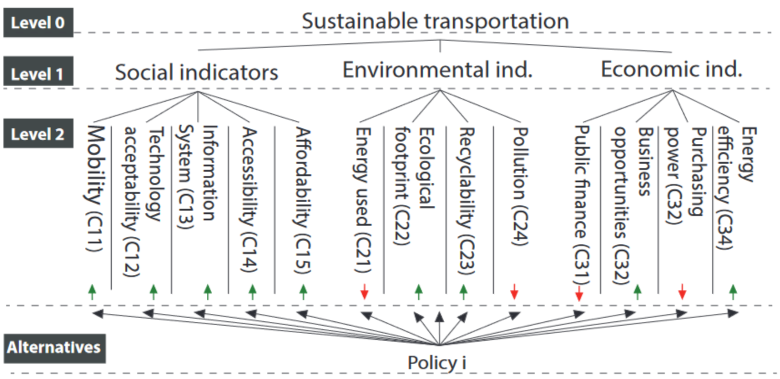

Figure 3. Hierarchical structure (adapted of Ngossaha et al. (2017)).

According to a literature review, there are numerous criteria and sub-criteria for evaluating transportation in terms of sustainable mobility. According to Ayadi et al. (2024), the selection of appropriate indicators presents a particular challenge due to the large number of available indicators. In her article, the author provides a literature review on different methods used for selecting criteria and sub-criteria for evaluating transportation in terms of sustainable mobility. This literature review allowed us to identify the three major criteria used in almost 90% of the cited articles, namely environmental, social, and economic criteria. An analysis with the experts enabled us to retain the hierarchical structure of work of Ngossaha et al. (2017) as it still reflects the current state of developing countries. The hierarchical structure is depicted in **Figure 3**. The green arrow indicates the criteria to maximize, while the red ones indicate the criteria to minimize for methods such as TOPSIS.

4.2.2. Criterion weights

In this section, the results of analysis using the fuzzy analytic hierarchy process (AHP) method is presented in order to determine the weights of the different criteria and sub-criteria. **Table 6** presents the judgments of different experts with AHP and **Table 7** the aggregated weights from different experts obtained using Equation (1).

Table 6. Judgments of different experts with AHP.

		Env	Soc	Eco
	DM1	(1.00, 1.00, 1.00)	(4.00, 5.00, 6.00)	(3.00, 4.00, 5.00)
Env	DM2	(1.00, 1.00, 1.00)	(1.00, 2.00, 3.00)	(0.17, 0.20, 0.25)
	DM3	(1.00, 1.00, 1.00)	(0.17, 0.20, 0.25)	(0.17, 0.20, 0.25)
	DM1	(0.17, 0.20, 0.25)	(1.00, 1.00, 1.00)	(0.25, 0.33, 0.50)
Soc	DM2	(0.33, 0.50, 1.00)	(1.00, 1.00, 1.00)	(0.13, 0.14, 0.17)
	DM3	(4.00, 5.00, 6.00)	(1.00, 1.00, 1.00)	(1.00, 2.00, 3.00)
	DM1	(0.20, 0.25, 0.33)	(2.00, 3.00, 4.00)	(1.00, 1.00, 1.00)
Eco	DM2	(4.00, 5.00, 6.00)	(6.00, 7.00, 8.00)	(1.00, 1.00, 1.00)
	DM3	(4.00, 5.00, 6.00)	(0.33, 0.50, 1.00)	(1.00, 1.00, 1.00)

Table 7 contains the aggregated judgments of experts using Equation (2). The consistency of the expert judgments is 0.04, indicating a strong consensus in the evaluation of the criteria. Additionally, **Table 8** also contains the fuzzy weights of the criteria obtained from the expert judgments using Equation (4).

Table 7. Aggregated judgments of experts.

	Env	Soc	Eco
Env	(1.00, 1.00, 1.00)	(0.87, 1.26, 1.65)	(0.44, 0.54, 0.68)
Soc	(0.61, 0.79, 1.14)	(1.00, 1.00, 1.00)	(0.31, 0.46, 0.63)
Eco	(1.47, 1.84, 2.29)	(1.59, 2.19, 3.17)	(1.00, 1.00, 1.00)

Table 8. Fuzzy weights of criteria.

Environmental	Social	Economic
(0.19, 0.28, 0.4)	(0.61, 0.79, 1.14)	(0.15, 0.22, 0.34)

These fuzzy weights capture the inherent uncertainty in subjective evaluations and provide a more comprehensive representation of expert perception. The defuzzification of fuzzy weights was performed using Equation (5).

To obtain the CRIP values of the criterion environmental, social, and economic with respect to the goal: $W_G = (0.273, 0.226, 0.501)^T$. These values represent the weights of the criteria more accurately and will facilitate the comparative analysis of different criteria. These weights will be used for determining the weights of the sub-criteria.

4.2.3. Weights of sub-criteria

The weights of the sub-criteria within the hierarchical structure were determined using the fuzzy AHP. Initially, the weights of the sub-criteria related to the social, environmental, and economic criteria were individually determined. Subsequently, the overall weight of each sub-criterion was obtained by multiplying the weight of the sub-criterion by the respective relative importance value (weight) of its parent criterion, as shown in **Table 9** and **Figure 4**.

Table 9. Overall weights of criteria and sub-criteria.

Criteria	Weight	Sub-criteria		Weight	Overall weight
Social	0.226	Mobility	(C11)	0.255	0.058
		Technology accessibility	(C12)	0.117	0.027
		Information system	(C13)	0.033	0.007
		Accessibility	(C14)	0.192	0.044
		Financial affordability	(C15)	0.403	0.091
Environmental	0.273	Energy used	(C21)	0.173	0.047
		Environmental impact	(C22)	0.154	0.042
		Recyclability	(C23)	0.323	0.048
		Pollution	(C24)	0.350	0.095
Economic	0.501	Public finances	(C31)	0.114	0.057
		Economic opportunity	(C32)	0.404	0.202
		Purchasing power	(C33)	0.096	0.048
		Energy efficiency	(C34)	0.386	0.193

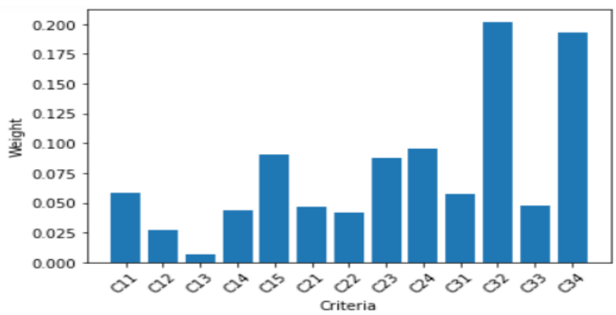

Figure 4. Global weights of criteria and sub-criteria.

The hierarchical structure for evaluating the criteria provides a clear understanding of their relative importance in the decision-making process. At the top level, the "economic" criterion was identified as the most important factor requiring improvements. This indicates that ensuring the economic aspects of the mobility system, particularly job creation, economic growth, and investment efficiency, is a major priority to enhance the sustainability and quality of the services. Among the sub-criteria, "economic opportunities" and "energy efficiency" were given very high importance, suggesting that the experts place great value on these aspects when evaluating mobility services. In contrast, the "information system" and "technology accessibility" criteria were ranked relatively less important. Although desirable, they do not seem as essential as "economic opportunities" and "energy efficiency" in the eyes of the experts. These rankings provide a valuable foundation to guide decisions on resource allocation and efforts aimed at improving the sustainability of mobility services.

4.2.4. Ranking of different alternatives

In this study, we employ a multicriteria approach to rank different alternatives. After determining the weights of the sub-criteria using the fuzzy AHP method, we utilize three different ranking methods: fuzzy AHP, fuzzy TOPSIS, and fuzzy PROMETHEE, with the respectively results presented in **Table 10–12**. Finally, we combine the results of these three methods using the Borda method to obtain a final ranking presented in **Table 13**.

In this study, the evaluation of the sub-criteria was first carried out using the fuzzy AHP method. The starting point was the development of a comparison matrix by each expert using a Saaty fuzzy triangular scale presented in **Table 4**, followed by an aggregation of the judgments of these experts using Equation (2). Since the judgment was consistent, a calculation of the fuzzy weights of each policy was carried out using Equation (4), followed by a defuzzification using Equation (5) for a total ranking of the alternatives. The results of this analysis are summarized in **Table 11**, with policy *P1* ranked as the best and policy *P4* as the worst.

Secondly a multi-criteria analysis of the variants was performed according to the TOPSIS method algorithm. First, the evaluations of the different experts were obtained and presented in **Table A1** in the Appendix. Subsequently, these judgments were aggregated and normalized using Equations (6), (7) and (8) respectively, and then corrected by weighting the individual decision factors. Next, the positive ideal solutions and the anti-ideal solutions were determined using the appropriate formula. In the next step, which was central to the selected method, the distances between the different variants and the ideal and anti-ideal solutions were calculated using Equations (11) and (12). The final ranking of the variants was established based on the global evaluation calculated according to Equation (13). The higher the value of the global evaluation, the better the ranking of the variant. This makes *P1* the best policy and *P3* the worst. The various results obtained are presented in **Table 11**.

Table 10. Ranking of alternatives by different method: Fuzzy AHP.

	Env	**Soc**	**Eco**		
Weights	**0.226**	**0.273**	**0.501**	**Weights**	**Rang**
*P*1	0.376	0.275	0.241	0.280	1
*P*2	0.266	0.238	0.233	0.242	2
*P*3	0.124	0.185	0.181	0.169	4
*P*4	0.080	0.121	0.151	0.126	5
*P*5	0.155	0.182	0.195	0.182	3

Table 11. Ranking of alternatives by different method: Fuzzy TOPSIS.

D_FPIS	D_FNIS	Cci	Rang
0.163	0.251	0.607	2
0.252	0.174	0.408	5
0.226	0.207	0.478	4
0.190	0.244	0.562	3
0.156	0.263	0.628	1

Table 12. Ranking of alternatives by different method: Fuzzy PROMETHEE respectively.

Flow+	Flow−	Net flow	Rang
1.03	0.14	0.88	1
0.79	0.30	0.48	2
0.54	0.52	0.01	3
0.48	0.69	−0.20	4
0.03	1.20	−1.17	5

At the end multi-criteria analysis was also carried out using the FUZZY PROMETHEE method, which is characterized by a different algorithm than the other methods used in this article. The starting point, as in the case of the TOPSIS method, was a matrix with evaluations of different criteria in light of the sub-criteria, as well as a set of weights obtained for these factors, presented in the **Table A2** in the Appendix. The type-1 function was selected from the 6 preference functions available for each criterion. It is noteworthy that this function expresses the strength of the decision maker's preferences, and its values range from 0 to 1. The various implementation steps of the PROMETHEE method, presented in step 7 of the methodology, were carried out and the results are presented in the corresponding tables.

The Borda method is used to combine these different results and obtain a final ranking. The position obtained by each alternative for each method was summed up as follows:

$$P1 = 5 + 4 + 5 = 14$$

$$P2 = 4 + 1 + 4 = 9$$

Once all choices have received their points, they can be ranked in descending order based on the total number of points they have accumulated.

Final result is presented in **Table 13**.

Table 13. Ranking of alternatives by different methods.

Method	Ranking
AHP	$P1 > P2 > P5 > P3 > P4$
TOPSIS	$P5 > P1 > P4 > P3 > P2$
PROMETHEE	$P1 > P2 > P3 > P4 > P5$
HYBRYD	$P1 > P5 = P2 > P3 > P4$

4.2.5. Sensitivity analysis

Sensitivity analysis is crucial to verify the stability of rankings. This analysis was conducted by modifying the criterion weights and applying steps 5, 6 and 7 of the propose methodology. Ten distinct scenarios, with their corresponding values presented in **Table 14**, were obtained by modifying the criterion weights.

Table 14. Different criteria values.

Scenario	Environmental	Social	Economic
	0.273	0.226	0.501
S1	0.373	0.226	0.401
S2	0.273	0.326	0.401
S3	0.276	0.276	0.401
S4	0.223	0.176	0.601
S5	0.373	0.126	0.501
S6	0.173	0.326	0.501
S7	0.340	0.330	0.330
S8	0.501	0.226	0.273
S9	0.273	0.501	0.226
S10	0.100	0.100	0.800

The first 4 scenarios modify the weight of the economic criterion while maintaining its first position. Scenario S1 preserves the weight of the social criterion and increases that of the environmental criterion, while Scenario S2 preserves the weight of the environmental criterion and modifies that of the social criterion. Scenarios S5 and S6 maintain the weight of the economic criterion and modify the other two. Scenario S7 assigns identical values to all criteria. In Scenarios S8 and S9, the economic criterion occupies the third position, and finally, scenario S10 assigns a significantly higher weight to the economic criterion compared to the other two. These various Scenarios provide an overview of the possible modifications.

The sensitivity analysis conducted for the proposed hybrid method, as depicted in **Figure 5**, reveals that the ranking of alternatives remains relatively stable despite variations in the weights of the social, environmental, and economic criteria. In most scenarios, alternative *P1* maintains its first position, closely followed by *P*2 and *P*5. Alternatives *P*3 and *P4* generally obtain lower positions.

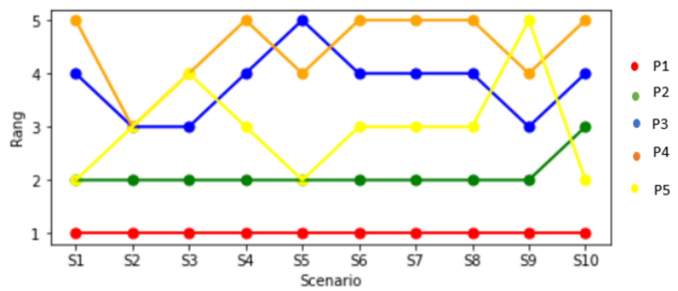

Figure 5. Sensitivity analysis of the proposed hybrid model.

To confirm the stability of the proposed model, a correlation verification using the Spearman's method as described in the studies of Biswas and Joshi (2023), Tešić and Marinković (2023) was performed. The following results were obtained for each scenario in **Table 15**.

Table 15. Spearman's rank correlation coefficient values.

Scenario	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10
Spearman values	1	0.75	1	0.93	1	0.93	0.93	0.93	1	0.93

These results all tend towards 1, which shows a good correlation between the different rankings, i.e., the slight change between the different rankings is not significant.

This suggests that the hybrid method is robust to a certain extent, as it maintains a consistent ranking of alternatives even when the criterion weights are changed. However, it is important to note that in some scenarios, alternatives *P3* and *P4* may be ranked equally, indicating some sensitivity of the ranking to weight variations.

Compared to other methods, the hybrid method offers several advantages. The main advantage of the hybrid method is that it combines the strengths of the different methods used AHP, TOPSIS, PROMETHEE to account for multiple aspects of evaluation. This enables a more robust and balanced ranking of alternatives. Additionally, the sensitivity analysis demonstrates that the hybrid method is relatively stable in the face of variations in criterion weights.

4.3. Discussion

The development and validation of a comprehensive fuzzy-based multi-criteria decision-making (MCDM) framework for sustainable urban mobility in developing countries address significant gaps in current urban planning methodologies. Traditional decision-making models often struggle with the complexity and uncertainty characteristic of developing regions, where data is frequently incomplete or unreliable, and subjective judgments are prevalent. By integrating fuzzy logic with MCDM techniques such as analytic hierarchy process (AHP), technique for order of preference by similarity to ideal solution (TOPSIS), and preference ranking organization method for enrichment evaluation (PROMETHEE), this study offers a flexible and nuanced approach. This framework allows for the comprehensive evaluation of multiple conflicting criteria, including cost, environmental impact, social acceptance, and technical feasibility, ensuring balanced and sustainable urban mobility solutions. The incorporation of the Borda method further enhances the robustness of decision-making by mitigating biases and dependencies in results.

The ranking of the alternatives is as follows: $P1$ is ranked first, followed by $P5$ and $P2$ sharing the second position, then $P3$ in the fourth position, and finally $P4$ in the fifth position. Compared to the rankings obtained by the other methods, some differences are observed. For example, the AHP method ranks $P2$ before $P5$, while the TOPSIS method ranks $P5$ before $P1$. The PROMETHEE method also ranks $P3$ before $P4$, while the hybrid method ranks $P3$ before $P4$. Based on the results obtained from the developed hybrid approach, compared to other decision-making methods and sensitivity analysis, it is observed that the obtained results are reliable and stable.

According to the results of the proposed approach, the construction of an administrative area is the most appropriate service to promote sustainable urban mobility in this country, while the construction of a recreational area is not suitable according to the needs of the population. Thus, the municipality can improve the mobility situation by carrying out this project.

The practical applicability and reliability of the proposed framework are demonstrated through a case study and sensitivity analysis, which validate the model under various scenarios. This real-world application provides decision-makers with a robust tool for systematically analyzing and prioritizing urban mobility alternatives, tailored to the specific challenges of developing countries. The insights gained have significant implications for policy and infrastructure planning, promoting a shift from short-term, conventional solutions to more strategic, long-term planning. By adopting advanced decision support tools, urban planners can make well-informed, sustainable, and context-appropriate transportation decisions, contributing to the development of more efficient, inclusive, and resilient urban transportation systems. However, the work recognizes limitations, especially in relation to the growing amount of information on urban mobility in developing countries and the adaptability of these data. To address these short comings, future plans include the integration of artificial intelligence and multi-criteria decision-making methods to improve the rigor and robustness of models and to further advance sustainable urban mobility planning in developing countries. Future research should also continue to refine this framework, explore its application in diverse urban contexts, and include a broader range of stakeholder perspectives to further strengthen its practical relevance and impact.

5. Conclusion

This paper presents a hybrid methodological framework designed to evaluate services aimed at promoting sustainable urban mobility in developing countries, addressing the diverse needs of decision-makers. Through a comprehensive literature review, appropriate sustainability indicators were identified, laying the foundation for the subsequent development of the hybrid approach. This approach combines fuzzy analytic hierarchy process (AHP), fuzzy technique for order of preference by similarity to ideal solution (TOPSIS), and fuzzy preference ranking organization method for enrichment evaluations (PROMETHEE), integrated using the Borda method to establish a more accurate ranking of alternatives. The results obtained from the sustainability analysis facilitate consensus-building among decision-makers, fostering an interactive process for reassessing judgments. Additionally, a sensitivity analysis was conducted to validate the obtained results, ensuring the reliability of the framework.

The practical implications of this study are significant for policymakers, urban planners, and civil society stakeholders. By leveraging the insights gleaned from the sustainability analysis, these stakeholders can formulate more effective urban mobility policies and projects tailored to the specific needs and challenges of developing countries. However, the work acknowledges limitations, particularly concerning the growing volume of information on urban mobility in developing countries and the adaptability of this data. To address these limitations, future plans include integrating artificial intelligence (AI) and multi-criteria decision-making methods (MCDM) to enhance the rigor and robustness of the model, further advancing sustainable urban mobility planning in developing countries.

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Appendix

Table A1. Judgments of experts for TOPSIS method.

		C11	**C12**	**C13**	**C14**	**C15**	**C21**	**C23**	**C22**	**C24**
	P1	(5, 7, 9)	(5, 7, 9)	(3, 5, 7)	(3, 5, 7)	(3, 5, 7)	(1, 3, 5)	(1, 3, 5)	(5, 7, 9)	(1, 3, 5)
DM1	P2	(5, 7, 9)	(5, 7, 9)	(1, 1, 3)	(5, 7, 9)	(7, 9, 9)	(5, 7, 9)	(3, 5, 7)	(3, 5, 7)	(5, 7, 9)
	P3	(5, 7, 9)	(3, 5, 7)	(1, 3, 5)	(3, 5, 7)	(5, 7, 9)	(3, 5, 7)	(7, 9, 9)	(7, 9, 9)	(1, 1, 3)
	P4	(5, 7, 9)	(5, 7, 9)	(3, 5, 7)	(5, 7, 9)	(3, 5, 7)	(5, 7, 9)	(3, 5, 7)	(5, 7, 9)	(7, 9, 9)
	P5	(7, 9, 9)	(5, 7, 9)	(7, 9, 9)	(7, 9, 9)	(3, 5, 7)	(5, 7, 9)	(1, 1, 1)	(1, 3, 5)	(7, 9, 9)
		C31	**C32**	**C33**	**C34**					
	P1	(1, 1, 3)	(1, 3, 5)	(1, 3, 5)	(3, 5, 7)					
	P2	(5, 7, 9)	(3, 5, 7)	(3, 5, 7)	(3, 5, 7)					
DM1	P3	(5, 7, 9)	(5, 7, 9)	(3, 5, 7)	(1, 1, 3)					
	P4	(1, 1, 3)	(3, 5, 7)	(5, 7, 9)	(5, 7, 9)					
	P5	(5, 7, 9)	(5, 7, 9)	(5, 7, 9)	(7, 9, 9)					
		C11	**C12**	**C13**	**C14**	**C15**	**C21**	**C23**	**C22**	**C24**
	P1	(5, 7, 9)	(5, 7, 9)	(5, 7, 9)	(5, 7, 9)	(7, 9, 9)	(1, 3, 5)	(1, 3, 5)	(5, 7, 9)	(1, 3, 5)
DM2	P2	(5, 7, 9)	(1, 3, 5)	(5, 7, 9)	(3, 5, 7)	(1, 3, 5)	(5, 7, 9)	(3, 5, 7)	(1, 1, 3)	(5, 7, 9)
	P3	(1, 3, 5)	(1, 1, 3)	(7, 9, 9)	(3, 5, 7)	(1, 3, 5)	(7, 9, 9)	(5, 7, 9)	(5, 7, 9)	(1, 3, 5)
	P4	(3, 5, 7)	(5, 7, 9)	(1, 3, 5)	(3, 5, 7)	(3, 5, 7)	(1, 3, 5)	(5, 7, 9)	(5, 7, 9)	(1, 3, 5)
	P5	(7, 9, 9)	(5, 7, 9)	(7, 9, 9)	(7, 9, 9)	(7, 9, 9)	(7, 9, 9)	(7, 9, 9)	(5, 7, 9)	(5, 7, 9)
		C31	**C32**	**C33**	**C34**					
	P1	(1, 1, 3)	(1, 3, 5)	(3, 5, 7)	(5, 7, 9)					
	P2	(5, 7, 9)	(5, 7, 9)	(5, 7, 9)	(3, 5, 7)					
DM2	P3	(5, 7, 9)	(5, 7, 9)	(3, 5, 7)	(3, 5, 7)					
	P4	(5, 7, 9)	(3, 5, 7)	(3, 5, 7)	(5, 7, 9)					
	P5	(5, 7, 9)	(5, 7, 9)	(5, 7, 9)	(5, 7, 9)					
		C11	**C12**	**C13**	**C14**	**C15**	**C21**	**C22**	**C23**	**C24**
	P1	(5, 7, 9)	(5, 7, 9)	(1, 3, 5)	(5, 7, 9)	(7, 9, 9)	(5, 7, 9)	(1, 3, 5)	(5, 7, 9)	(5, 7, 9)
	P2	(7, 9, 9)	(7, 9, 9)	(1, 1, 3)	(1, 3, 5)	(1, 3, 5)	(3, 5, 7)	(5, 7, 9)	(3, 5, 7)	(1, 3, 5)
DM3	P3	(3, 5, 7)	(1, 3, 5)	(7, 9, 9)	(5, 7, 9)	(1, 3, 5)	(5, 7, 9)	(5, 7, 9)	(5, 7, 9)	(5, 7, 9)
	P4	(3, 5, 7)	(1, 3, 5)	(5, 7, 9)	(5, 7, 9)	(3, 5, 7)	(1, 1, 3)	(1, 1, 3)	(3, 5, 7)	(1, 3, 5)
	P5	(5, 7, 9)	(7, 9, 9)	(5, 7, 9)	(5, 7, 9)	(5, 7, 9)	(5, 7, 9)	(7, 9, 9)	(7, 9, 9)	(7, 9, 9)
		C31	**C32**	**C33**	**C34**					
	P1	(5, 7, 9)	(3, 5, 7)	(3, 5, 7)	(3, 5, 7)					
	P2	(1, 1, 3)	(3, 5, 7)	(3, 5, 7)	(1, 1, 3)					
DM3	P3	(3, 5, 7)	(3, 5, 7)	(3, 5, 7)	(5, 7, 9)					
	P4	(5, 7, 9)	(3, 5, 7)	(3, 5, 7)	(3, 5, 7)					
	P5	(7, 9, 9)	(7, 9, 9)	(7, 9, 9)	(7, 9, 9)					

Table A2. Judgments of experts for PROMETHEE method.

		C11	C12	C13	C14	C15	C21	C22	C23	C24	C31	C32	C34	C34
	DM1	G	G	M	M	M	P	P	G	P	VP	P	P	M
*P*1	DM2	G	VG	G	G	VG	P	P	G	P	VP	P	M	G
	DM3	G	G	P	G	VG	G	P	G	G	G	M	M	M
	DM1	G	G	VP	G	VG	G	M	M	G	G	M	M	M
*P*2	DM2	G	P	G	M	P	G	M	VP	G	G	G	G	M
	DM3	VG	VG	VP	P	P	M	G	M	P	VP	M	M	VP
	DM1	G	M	P	M	G	M	VG	VG	VP	G	G	M	VP
*P*3	DM2	P	VP	VG	M	P	VG	G	G	P	G	G	M	M
	DM3	M	P	VG	G	P	G	G	G	G	M	M	M	G
	DM1	G	VG	M	G	M	G	M	G	VG	VP	M	G	G
*P*4	DM2	M	G	P	M	M	P	G	G	P	G	M	M	G
	DM3	M	P	G	G	M	VP	VP	M	P	G	M	M	M
	DM1	VG	VG	VG	VG	M	G	VP	P	VG	G	G	G	VG
*P*5	DM2	VG	G	VG	VG	VG	VG	VG	G	G	G	G	G	G
	DM3	G	VG	G	G	G	G	VG	VG	VG	VG	VG	VG	VG

Table A3. Compute the weighted normalized fuzzy matrix.

	C11	C12	C12	C13	C14	C15	C21
*P*1	(9.1, 17.8, 32.7)	(4.00, 8.80, 17.20)	(0.20, 1.60, 4.00)	(3.8, 12.1, 25.8)	(8.60, 31.30, 57.00)	(1.20, 7.60, 24.30)	(9.1, 17.8, 32.7)
*P*2	(9.1, 19.5, 36.3)	(0.80, 7.30, 17.20)	(0.00, 0.90, 4.00)	(1.30, 9.50, 25.80)	(2.90, 20.40, 57.00)	(3.60, 11.00, 24.30)	(9.1,19.5,36.3)
*P*3	(1.8, 12.7, 32.7)	(0.00, 3.50, 12.00)	(0.20, 2.20, 4.40)	(3.80, 10.80, 25.80)	(2.90, 17.70, 51.30)	(3.60, 12.20, 27.00)	(1.8,12.7,32.7)
*P*4	(5.5, 14.4, 32.7)	(0.80, 7.30, 17.20)	(0.20, 1.60, 4.00)	(3.80, 12.10, 25.80)	(8.60, 20.40, 39.90)	(0.00, 6.40, 24.30)	(5.5,14.4,32.7)
*P*5	(9.1, 21.2, 36.3)	(4.00, 9.60, 17.20)	(1.20, 2.60, 4.40)	(6.30, 15.90, 28.60)	(8.60, 28.60, 57.00)	(5.90, 13.40, 27.00)	(9.1,21.2,36.3)

	C22	C23	C24	C31	C32	C33	C34
*P*1	(0.90,4.4, 13.00)	(10.1, 22.4, 47.6)	(2.00, 15.50, 52.2)	(0.00, 3.4, 15.90)	(2.60, 14.70, 43.3)	(0.60, 4.10, 10.10)	(7.6, 22.20, 52.50)
*P*2	(2.80,8.4, 23.50)	(0.0, 11.7, 37.0)	(2.00, 20.30, 52.2)	(0.00, 5.60, 15.90)	(7.90, 22.80, 55.70)	(1.90, 5.40, 13.00)	(0.00, 14.3, 40.9)
*P*3	(4.60,11.3, 26.1)	(10.1,24.5, 52.8)	(0.00, 13.10, 52.2)	(2.20, 7.10, 15.90)	(7.90, 25.40, 55.70)	(1.90, 4.80, 10.10)	(0.00, 17.0, 52.5)
*P*4	(0.0,6.4, 23.5)	(6.0, 20.3, 47.6)	(2.0, 17.90, 58.00)	(0.00, 5.60, 15.90)	(7.90, 20.10, 43.30)	(1.90, 5.40, 13.00)	(7.60, 24.8, 52.5)
*P*5	(0.0, 9.3, 26.1)	(2.0, 20.3, 52.8)	(9.9, 29.8, 58.0)	(3.7, 8.60, 17.70)	(13.2, 30.80, 61.90)	(3.20, 7.30, 14.40)	(12.6, 32.6, 58.4)