

Article

Research on the Significance of Criteria Influencing the Deployment of Micromobility Devices in Cities Using Multi-Criteria Decision-Making (MCDM) Methods

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Abstract

Urban mobility is increasingly affected by air pollution and traffic congestion caused by conventional private vehicles, as well as by insufficient flexibility of public transport. Micromobility devices (MMDs) can mitigate these and other negative impacts on quality of life due to their distinctive characteristics, the significance of which is investigated in this research. To address these challenges facing the modern city, a system of 15 hierarchically unstructured criteria influencing the deployment of MMDs in urban areas was established. The relative weights of these criteria were calculated based on the assessments of 16 experts and the criterion weights were determined using four multi-criteria decision-making (MCDM) methods: ARTIW-L (Average Rank Transformation into Weight—Linear), ARTIW-N (Average Rank Transformation into Weight—Non-Linear), DPW (Direct Percentage Weight), and AHP (Analytic Hierarchy Process). The results indicate that the expert judgments are consistent, as Kendall's coefficient of concordance 0.406 is 3.8 times greater than the minimum value of 0.106 (at a significance level 0.05 and 14 degrees of freedom). In addition, the consistency ratios (C.R.) calculated from the AHP pairwise comparison matrices were below 0.1. The demonstrated consistency of the expert judgements and the compatibility of all matrices justify adopting the average of the relative weights obtained using the four MCDM methods as the final solution. According to the experts, the most important criteria for MMD deployment are travel safety (0.1336), travel duration (0.1302), the influence of infrastructure quality on comfort (0.0841), impact on health (0.0805), and the cost of purchasing an MMD (0.0713), while the remaining criteria are of lower significance. Based on the research results it is expected that the identified micromobility implementation measures will be useful for decision-makers and urban development planners.



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1. Introduction

Urban mobility is usually associated with travel by private vehicles, public transport, or taxis. In recent years, however, various types of so-called micromobility devices (MMDs) have gained substantial popularity [1]. One of the most widely used MMDs is the bicycle;

however, the development of low-power electric drives has significantly expanded the range of alternatives for short-distance travel [2,3]. In some countries of North America and Europe, the use of MMDs has increased by up to 40% within a few years during the post-pandemic period, and further growth is expected [4,5]. In this research, MMDs include walking, electric scooters (e-scooters), bicycles, electric bicycles (e-bikes), and a group of other devices (e.g., hoverboards, electric unicycles). Although walking is not typically considered an MMD, it is included in this research as a viable alternative to motorized transport and public transport. While previous research shows that mini electric vehicles and various modified powered scooters represent some of the most promising forms of micromobility [6], such vehicles are not considered in this research. This exclusion is justified by the fact that mini electric vehicles do not provide a distinct alternative form of mobility and require the same road infrastructure as conventional cars.

Although traffic congestion and the need of flexible mobility are the primary drivers of MMD deployment, micromobility also contributes to reducing transport-related pollution in cities [7,8]. This trend is transforming both the concept of urban transport and the efficiency of transport systems, supporting a shift toward more sustainable transportation models, including new hydrogen-powered bicycles based on fuel cell technology [9,10]. At the same time, urban transport is becoming more diverse and less predictable, thereby creating new challenges for traffic management and organization. However, the use of various MMDs requires the development and rapid expansion of dedicated infrastructure that ensures comfortable and safe mobility [11,12]. Safety is a particularly critical aspect, as MMD users are considered vulnerable road users and are therefore susceptible to injuries even in minor collisions [13]. Unfortunately, the number of injuries, various types of trauma, and fatalities have increased alongside the expansion of MMD use [14,15]. Due to their small wheels and lightweight construction, e-scooters are subject to intense vibrations, which reduce riding comfort and may compromise stability [16,17]. Consequently, road safety authorities have introduced several regulatory measures, including restricted-access urban areas and speed control measures [18,19].

Ignaccolo et al. [20] grouped different criteria into five categories (coherence and accessibility, linearity, safety and security, attractiveness and intermodality, and comfort) together with corresponding design recommendations to enable the redesign of urban spaces so they can accommodate this new form of mobility as MMDs feature different size and technology. These recommendations were developed for Italian cities; however, they are consistent with general European guidelines. Four expert-based evaluation methods have shown that road surface type and quality, along with road and street design, are the primary factors affecting e-scooter safety [21]. These findings are strongly related to the design characteristics of e-scooters, which typically feature small-diameter wheels and a short steering-axis caster, resulting in high sensitivity to pavement irregularities. Moreover, vibration levels caused by the riding surface and e-scooter construction (e.g., frame design and tire inflation pressure) directly affect rider comfort sensation [22]. Prolonged discomfort has been associated with increased fatigue and reduced attentiveness.

Several aspects are associated with the risky use of MMDs. Firstly, these devices are often equipped with relatively powerful electric drives, enabling users, regardless of their physical fitness level, to travel very dynamically and smoothly [22,23]. In addition, electric drives operate very quietly, which may lead to sudden and unexpected encounters with pedestrians, thereby increasing the risk of collisions [24].

In addition to infrastructure and technical factors, the safe use of micromobility devices also depends on user behavior and cultural aspects. Based on e-survey data from 39 countries, Delavary et al. [25] found that younger individuals and males are more likely to use MMDs and engage in risky behaviors, which are further associated with

student status, prior crashes, and permissive safety attitudes. The findings emphasize the need for targeted safety interventions that combine infrastructure improvements with behavior-focused strategies.

The specifics of using micromobility devices, especially dynamic ones such as e-bikes or e-scooters, differ across age groups. Promoting e-bikes for sustainable transport among adults aged 65 and older has potential but faces several challenges [26]. A Flemish survey revealed key benefits like less physical effort, longer travel distances, and substitution for regular bikes or cars. However, challenges include the bikes' heavy weight and safety concerns, with notable gender differences. These results highlight the importance of policies that enhance benefits, improve safety, and assess the feasibility of e-bikes in areas less conducive to cycling.

In recent years, numerous studies have examined the experiences of different cities and regions in integrating micromobility measures into their transport systems [27–34]. These studies indicate that micromobility usage patterns are strongly influenced by general factors such as weather conditions, fleet size, infrastructure quality, and local regulations, with precipitation consistently reducing demand. User preferences also exhibit considerable variation: while some travelers embrace micromobility as part of a multimodal travel lifestyle, others remain hesitant due to safety concerns or lack of familiarity with these modes. Despite such differences, existing research highlights that well-planned micromobility systems, supported by appropriate infrastructure and regulation, can significantly improve urban mobility and reduce dependence on private cars. Conversely, the growing popularity of e-scooters has intensified debates over regulatory measures aimed at mitigating their negative externalities [35]. The findings suggest that mixed regulatory effects—safety measures increase inclination of e-scooter use, whereas parking restrictions, high fares, and fines reduce it. Moreover, perceived road unsafety lowers usage intentions, with stronger policy support observed among individuals who consider e-scooters unsafe. Additionally, data collected from micromobility users is increasingly employed to develop methodologies for identifying the most hazardous infrastructure nodes, thereby informing targeted safety interventions [36].

A variety of mathematical and analytical methods are applied to refine and prioritize smart city features and to advance MMDs. These urban-related indicators cover pollution control, energy and environmental resources, community well-being, eco-friendly transport, and social cohesion [37,38]. Research on micromobility increasingly relies on socio-technical and configurational methods, particularly the Multi-Level Perspective (MLP) combined with Qualitative Comparative Analysis (QCA), to explain complex causal mechanisms underlying the use and non-use of micromobility services [39]. Multi-criteria decision-making (MCDM) approaches—such as APPRESAL, fuzzy BWM–CoCoSo, AHP/Fuzzy, Fuzzy TOPSIS, Fuzzy VIKOR, and Fuzzy GRA—are widely applied to evaluate micromobility performance, user satisfaction, sustainability, and policy alternatives under conditions of uncertainty [40–42]. In general, modern practice records the application of over 200 MCDM methods to evaluate and identify the optimal alternative across diverse fields [43]. Sustainability assessments of broader mobility projects also employ fuzzy ideal-solution methods to rank alternatives in situations where precise data are limited and stakeholder perspectives differ [44]. At the neighborhood-scale, suitability analyses commonly apply multicriteria indices to identify optimal locations and system types (e.g., station-based vs. free-floating), using simple scoring schemes that facilitate practical decision-making even when data are scarce [45]. Several studies emphasize that integrating micromobility within Mobility-as-a-Service (MaaS) ecosystems requires dedicated MCDM assessment frameworks to ensure accessibility for vulnerable social groups [46].

The Classical Analytic Hierarchy Process (AHP) was applied to support decision-making in selecting the most appropriate micromobility system type for a given study area [45]. For further analysis, the following categories were established: population characteristics, travel behavior characteristics, land-use features, weather conditions, esthetic attractiveness, road network and comfort, road safety, security, connectivity and inter-modality, attractiveness compared to alternative modes, health and environmental benefit; however, weather conditions maintained the same relative importance when the AHP method was applied across different types of urban areas.

Many methods prioritize structured evaluation but lack integration with real-world usage data, resulting in potential gaps between modeled insights and actual rider behavior or operational realities. Moreover, most frameworks concentrate on early-stage planning or high-level assessment, providing limited guidance for the continuous monitoring or adaptation of micromobility systems over time.

Alternative research employing surveys, in situ tests with GPS/GIS and traffic analysis was conducted to identify the factors influencing route and infrastructure choices in micromobility [47]. The study highlights key determinants such as safety, comfort, connectivity, and infrastructure quality, while also identifying significant gaps, particularly regarding e-bikes and e-scooters. Taiwan-focused research, in one of the world's highest scooter-density regions, was conducted by integrating four key dimensions and 16 criteria through a rigorous combination of literature review, expert input, and advanced analytical methods [48]. The analysis indicates that service attributes related to user convenience, trust, and responsiveness should be prioritized; moreover, consumers appreciate convenient and secure payment systems and loyalty programs. Finally, a decision tree algorithm from a machine learning approach was applied to identify the factors contributing to risky use of MMDs [49]. After processing survey data, the results show that helmet use and trip type are the primary safety factors, following age, gender, and riding location.

The issue of micromobility in urbanized areas is relatively new, with its development policy reaching cities only in the past decade and gaining momentum in the post-pandemic period, when different modes of mobility acquired broader significance. Therefore, expert opinions and their alignment in proposing the most appropriate directions for policy development are particularly important in urban life. Moreover, addressing this multifaceted issue involves the advancement of the integrated application of MCDM methods, which also highlights the scientific relevance of the research. During the deployment of MMDs, it is important to recognize that MMDs do not function solely as substitutes for public transport, but can also be effectively incorporated into public transportation networks. From this perspective, a survey conducted with 25 transportation and urban professionals in Europe and North America indicated that high-quality public transport, dedicated micromobility lanes, supportive land-use patterns, and appropriate policy frameworks form the foundation for the successful integration of these urban mobility elements [50]. In their research, Nogueira et al. [51] predict that the success of MMD deployment is associated with public participation beyond consultation and robust monitoring; however, challenges remain regarding the durability of temporary measures, political risk, and limited administrative capacity.

The aim of the research is to develop a structured system of criteria influencing the deployment of urban micro-mobility devices and, based on expert-driven quantitative assessment using multi-criteria decision-making (MCDM) methods, to determine the relative weights of these criteria and conduct a comparative analysis. The impact of the research is directly linked to urban transport system challenges—reducing traffic congestion, as well as transport-related pollution and noise. These issues can be addressed through the effective implementation of micromobility solutions that are convenient and accessible for as large a share of urban residents as possible.

2. Materials and Methods

2.1. Required Characteristics of Micromobility Devices (MMDs)

A scientific literature analysis (including journal articles and conference proceedings), combined with the authors' professional experience, enabled the identification and systematic classification of the key criteria influencing the deployment of MMDs and the selection among alternative micromobility modes. The set of MMD criteria examined in the current research is presented in Table 1.

Table 1. Criteria influencing the deployment of MMDs in urban areas.

Abbreviation	Description of Criteria
A	Impact on health
B	Travel time
C	Infrastructure installation (construction) and maintenance cost
D	Cost of purchasing an MMD
E	Travel safety
F	Influence of ambient air temperature
G	Possibility of carrying luggage
H	Protection of MMDs when not in use
I	Environmental impact of MMDs
J	Influence of infrastructure quality on comfort
K	Operating costs of MMDs
L	Suitability for users of different age groups
M	State support and incentives for the purchase of MMDs
N	Possibility of carrying multiple users
O	Impact of precipitation on travel

The MMD criteria presented in Table 1 vary in their level of importance for deployment in the city. The assumption made it possible to determine the actual significance of the criteria by applying expert-based research methods. The experts' knowledge, experience, and competence in assessing the importance of the selected criteria were quantitatively captured through a structured questionnaire, the structure of which was designed and prepared by the authors.

2.2. Experts

A panel of 16 experts was formed to participate in the study. A relatively small number of experts is entirely typical in expert surveys and studies of this nature [52,53]. The panel comprised 12 researchers holding doctoral degrees with expertise in transport engineering and civil engineering, as well as 4 doctoral students specializing in these fields; therefore, the experts' assessments can be considered sufficiently accurate and reliable for the current research. The professional activities of all experts involved in the study are related to the land transport system, including its planning, design, development, or management. Moreover, all experts operate within a similar geographical region; therefore, their individual opinions do not reflect differing perceptions of urban development. On this basis, a consistent level of expertise is maintained, allowing the data provided by the experts to be treated with equal significance (no preference was given), while the relatively homogeneous disciplinary composition of the expert group is not expected to introduce any significant bias affecting the results. The assembled expert panel was capable of addressing the research problem effectively and consistently. As the individual competence of each expert was not assessed separately, all expert judgments were assigned equal weight, with no preferential weighting applied. The use of expert judgement was necessitated by the lack of alternative data sources. The experts were instructed to assess the significance of the MMD criteria in such a way as to avoid tied rankings, as the presence of ties would complicate subsequent calculations. The selection of experts was not restricted by institutional affiliation related to the development of micromobility devices or urban

mobility infrastructure. All experts operate within a similar geographical region; therefore, individual opinions do not reflect differing perceptions of urban development. On this basis, a consistent level of expertise among the experts was ensured, allowing equal significance to be attributed to the data they provided in the study.

2.3. MCDM Methods Used in the Research

Each expert ($e = 1, 2, \dots, n$) evaluated the significance of all MMD criteria ($i = 1, 2, \dots, m$) using a structured questionnaire. The evaluation was carried out by assigning ranks R_{ie} , percentage weights P_{ie} , and pairwise comparison intensity values a_{ij} derived from the Analytic Hierarchy Process (AHP). These criterion significance values were subsequently used as input in four multi-criteria decision-making (MCDM) methods to calculate the subjective normalized relative weights of the criteria. During the completion of the criteria importance assessment questionnaire using the AHP method, the process was monitored by one of the authors of this article. This approach helped prevent major errors in questionnaire completion arising from violations of the transitivity condition of the criteria.

The significance of each criterion, expressed in terms of ranks (R_{ie}), percentage weights (P_{ie}), or relative weights derived using the AHP method, inevitably varies among experts. The magnitude of variation in the criterion ranks is quantified using the standard deviation σ_{Ri} , variance σ_{Ri}^2 , and the coefficient of variation V_{Ri} . Greater consistency among expert judgements is associated with lower variability in the estimated values. In empirical studies, some values assigned to criteria by experts may differ substantially from other assessments and from the mean value $\bar{R}_i$; such observations are classified as outliers. The idea of removing outliers from expert questionnaire data, which forms the basis of the calculation methodology, was introduced through the novel CIBRO (Criteria Importance but Rejected Outliers) method [54]. Criterion rank values R_{ie} that fall outside a predefined interval $\bar{R}_i \pm 3\sigma_{Ri}$ are considered outliers and may be excluded from further analysis. If at least one assessment provided by the e -th expert meets the definition of an outlier, all rank values R_{ie} assigned by the expert are excluded. Subsequent calculations are then performed without the ranks and other significance estimates provided by the excluded expert.

2.3.1. Consistency of Expert Team Opinions

The degree of consistency (non-contradiction) among expert judgements was assessed using Kendall's rank correlation method [55]. For this purpose, the sums of ranks assigned $\sum_{e=1}^n R_{ie}$ to each i -th criterion and their corresponding mean values $\bar{R}_i$ were calculated according to Equation (1):

$$\bar{R}_i = \sum_{e=1}^n R_{ie} / n, \quad (1)$$

where R_{ie} denotes the rank (position according to significance) assigned by the e -th expert ($e = 1, 2, \dots, n$) to the i -th criterion ($i = 1, 2, \dots, m$); and n is the number of experts.

In the absence of tied ranks, the consistency of expert judgements is measured using Kendall's coefficient of concordance W , which is calculated according to Equation (2) and reflects the statistical consistency of the experts' assessments:

$$W = \frac{12S}{n^2(m^3 - m)}, \quad (2)$$

where m is the number of criteria influencing the deployment of MMDs, and S is the sum of squared deviations of the sums of the criterion ranks $\sum_{e=1}^n R_{ie}$ from the overall mean rank $\bar{R} = \frac{n(m+1)}{2}$, calculated according to Equation (3):

$$S = \sum_{i=1}^m \left(\sum_{e=1}^n R_{ie} - \bar{R} \right)^2. \quad (3)$$

When more than 7 criteria are compared ($m \geq 7$), the consistency of expert judgements is evaluated using Equation (4) by calculating the chi-square random variable χ^2 [56]:

$$\chi^2 = Wn(m-1). \quad (4)$$

The calculated χ^2 statistic is compared with its critical (tabulated) value $\chi_{\alpha, \nu}^2$, which depends on the selected significance level α —typically $\alpha = 0.05$ —or the more stringent $\alpha = 0.01$, and the number of degrees of freedom $\nu = m - 1$.

The consistency of expert judgements can also be assessed by calculating the minimum value of Kendall's coefficient of concordance $W_{\min}$, using Equation (5) [57]:

$$W_{\min} = \frac{\chi_{\alpha, \nu}^2}{n(m-1)}. \quad (5)$$

The ratio of Kendall's empirical coefficient of concordance W to its minimum value $W_{\min}$ is equal to the χ^2 and $\chi_{\alpha, \nu}^2$ ratio, referred to as the compatibility coefficient k_c , which is calculated using Equation (6):

$$k_c = \frac{W}{W_{\min}} = \frac{\chi^2}{\chi_{\alpha, \nu}^2}. \quad (6)$$

For the criteria rankings, the expert panel with aligned judgements obtained a compatibility coefficient $k_c > 1$.

2.3.2. Calculation of Relative Criterion Weights Using the ARTIW-L Method

The significance of the criteria influencing the deployment of MMDs, derived from the average ranks $\bar{R}_i$, is quantified using normalized relative weights $\omega_i^{\text{ARTIW-L}}$ by applying the Average Rank Transformation into Weight—Linear (ARTIW-L) method [58]:

$$\omega_i^{\text{ARTIW-L}} = \frac{m+1-\bar{R}_i}{\sum_{i=1}^m \bar{R}_i}. \quad (7)$$

The relative weights of criteria $\omega_i^{\text{ARTIW-L}}$ are linearly and inversely dependent on the average ranks $\bar{R}_i$ of these criteria, with a coefficient of determination $R^2 = 1$ [59].

2.3.3. Calculation of Relative Criterion Weights Using the ARTIW-N Method

The significance of the criteria influencing the deployment of MMDs in the city is determined using Equation (8) by calculating the relative weights of these criteria $\omega_i^{\text{ARTIW-N}}$ from the average criterion ranks $\bar{R}_i$, applying the Average Rank Transformation into Weight—Non-linear (ARTIW-N) method [60]:

$$\omega_i^{\text{ARTIW-N}} = \frac{\min_i \bar{R}_i}{\bar{R}_i \cdot \sum_{i=1}^m \frac{\min_i \bar{R}_i}{\bar{R}_i}}, \quad (8)$$

where $\min_i \bar{R}_i$ denotes the lowest average rank corresponding to the most important MMD criteria.

The relative weights of the criteria $\omega_i^{\text{ARTIW-N}}$ are inversely and non-linearly related to the average ranks $\bar{R}_i$, exhibiting a perfect functional dependence with a coefficient of determination $R^2 = 1$.

2.3.4. Calculation of Relative Criterion Weights Using the DPW Method

When each expert evaluates the significance of the criteria in the questionnaire, not only by assigning ranks (R_{ie}) but also by specifying percentage weights (P_{ie}), these percentage weights are used to determine the significance of the criteria by applying the Direct Percentage Weight (DPW) method [61]. Using the DPW method, the relative weight ω_i^{DPW} of each criterion is calculated according to Equation (9):

$$\omega_i^{\text{DPW}} = \frac{\sum_{e=1}^n P_{ie}}{100n}, \quad (9)$$

where P_{ie} denotes the percentage weight assigned to the i -th criterion ($i = 1, 2, \dots, m$) by the e -th expert ($e = 1, 2, \dots, n$), with ($\sum_{i=1}^m P_{ie} = 100.0\%$), and n is the number of experts in the panel.

The relative weights of the criteria ω_i^{DPW} calculated using the DPW method are inversely and linearly correlated with the average ranks of the criteria $\bar{R}_i$. The coefficient of determination for this relationship is $R^2 < 1$.

2.3.5. Calculation of Relative Criterion Weights Using the AHP Method

The Analytic Hierarchy Process (AHP) is widely used in scientific research to evaluate the significance of criteria for the object under study [62]. This method is particularly suitable for estimating relative criterion weights when the object under analysis comprises 5–9 criteria [63]. An experienced researcher may successfully assess more than 10 criteria; however, the number of criteria should not be fewer than 3. The AHP is a theory of measurement based on pairwise comparisons and relies on expert judgements to derive priority scales. These scales are used to quantify intangible criteria in relative terms. The pairwise comparisons are performed using a fundamental 9-point scale of absolute judgements, which expresses the extent to which one element dominates another with respect to a given attribute [64].

Each expert performs pairwise comparisons of the criteria $i, j = 1, 2, \dots, m$, using a square reciprocal matrix $\mathbf{A} = [a_{ij}]_{m \times m}$ assigning an intensity of importance to each comparison $a_{ij} = 1/a_{ji}$. Each criterion listed in the left-hand row of the matrix is compared with the criterion indicated in the corresponding column. Prior to conducting the pairwise comparisons, it is recommended that all criteria be preliminary ranked and arranged in descending order of importance, from the most important to the least important. When constructing the pairwise comparison matrix, the transitivity condition must be satisfied. The AHP method is optimal for evaluating 5–9 criteria; however, it also allows for the assessment of a larger number of criteria. As the number of criteria increases, completing the matrix becomes more complex, but an experienced expert can fill it out correctly.

After evaluating all criteria, the eigenvector ω_{ie}^{AHP} for each matrix row is calculated according to Equation (10) and is taken as the priority value of the i -th criterion assigned by the e -th expert:

$$\omega_{ie}^{\text{AHP}} = \frac{\sqrt[m]{\prod_{j=1}^m a_{ij}}}{\sum_{i=1}^m \sqrt[m]{\prod_{j=1}^m a_{ij}}}. \quad (10)$$

Here a_{ij} denotes the level of relative importance of the criteria compared in pairs, which may range from 1/9 to 9 when the full fundamental scale is applied.

After calculating the priority vector for each criterion in the pairwise comparison matrix ω_{ie}^{AHP} , the consistency of the matrix must be assessed using the consistency ratio (C.R.). To determine its value, the consistency index (C.I.) is first calculated according to equation:

$$C.I._e = \frac{\lambda_{\max e} - m}{m - 1}, \quad (11)$$

where $\lambda_{\max e}$ denotes the largest eigenvalue of the matrix constructed from the criteria evaluated by the e -th expert, calculated according to Equation (12):

$$\lambda_{\max e} = \frac{1}{m} \sum_{i=1}^m \frac{\sum_{j=1}^m a_{ij} \cdot \omega_{ie}^{AHP}}{\omega_{ie}^{AHP}}. \quad (12)$$

The ratio of the consistency index $C.I._e$ to the random index $R.I.$ must not exceed the accepted threshold value. The random index, which depends on the size of the square matrix (i.e., the number of comparable criteria m), is provided in tabulated form [62] or, for larger matrices ($m > 15$), can be calculated using an equation [65].

The ratio of $C.I.$ to the random $R.I.$ for a matrix of the same order is referred to as the consistency ratio (C.R.). The C.R. should to be kept sufficiently small, typically below 10%, indicating that deviations from non-random (i.e., informed) judgements are less than one order of magnitude [63].

If the consistency ratio C.R. of a matrix exceeds 0.1, the matrix must be revised by the expert or the researcher conducting the study to reduce the C.R. below 0.1; otherwise, the matrix is rejected.

The arithmetic mean $\bar{\omega}_{ie}^{AHP}$ of the priority vectors of the criteria ω_{ie}^{AHP} derived from matrices accepted by the expert panel, calculated according Equation (13), represents the overall relative weight of the i -th criterion as determined using the AHP method:

$$\bar{\omega}_{ie}^{AHP} = \frac{\sum_{e=1}^n \omega_{ie}^{AHP}}{n}, \quad (13)$$

where n denotes the number of experts.

2.3.6. Averaging of Criterion Weights Calculated Using Different Methods

There is no theoretical basis for identifying any of the applied MCDM methods as more reliable than the others. Consequently, the relative weights of the criteria obtained using different MCDM methods are considered equally valid and are not assigned preferential importance. Therefore, the arithmetic mean of these relative weights, calculated according to Equation (14), is adopted as the final solution to the problem:

$$\omega_i = \frac{\sum_{k=1}^r \omega_{ik}}{r}, \quad (14)$$

where ω_{ik} is the relative weight of criterion i -th calculated using the k -th MCDM method ($k = 1, 2, \dots, r$); and r is the number of methods used in the research.

This averaged value is considered more reliable than any single value obtained using an individual method.

2.3.7. Calculation of the Accuracy of the Results

If the ranks R_{ie} of each criterion follow a normal distribution $\sigma_{R_i}^2$ and their variances are statistically equal (homogeneous), the total variance of the significance estimates (ranks) for the entire object under investigation, namely, the set of criteria representing criteria

influencing the deployment of micromobility in the city, comprising m criteria, is calculated using Equation (15):

$$\sigma_R^2 = \frac{\sum_{i=1}^m \sigma_{Ri}^2}{m}. \quad (15)$$

The conformity of the ranks R_{ie} of each i -th criterion to the normal distribution is assessed using the skewness and kurtosis. The absolute values of skewness $|Sk|$ and kurtosis $|Ku|$ coefficients must be lower than their respective standard deviations s_{Sk} and s_{Ku} , multiplied by 3 and 5 [37], i.e., $|Sk| < 3s_{Sk}$ and $|Ku| < 5s_{Ku}$. The standard deviations s_{Sk} and s_{Ku} of skewness and kurtosis depend solely on the sample size, namely the number of experts n , who evaluated each criterion, and are calculated using Equations (16) and (17):

$$s_{Sk} = \sqrt{\frac{6n(n-1)}{(n-2)(n+1)(n+3)}}, \quad (16)$$

$$s_{Ku} = \sqrt{\frac{24n(n-1)^2}{(n-3)(n-2)(n+3)(n+5)}}. \quad (17)$$

The homogeneity of variances of the criterion ranks σ_{Ri}^2 is tested using Cochran's test [66]. According to this test, the test statistic $\hat{G}_{\max}$ is calculated using Equation (18):

$$\hat{G}_{\max} = \frac{\max_i \sigma_{Ri}^2}{\sum_{i=1}^m \sigma_{Ri}^2}, \quad (18)$$

where $\max_i \sigma_{Ri}^2$ denotes the maximum rank variance calculated among all criteria.

Cochran's test statistic $\hat{G}_{\max}$ must be lower than its critical tabulated value $G_C(\alpha; m; \nu)$, which depends on the selected significance level α , the number of compared variances (criteria) m , and the number of degrees of freedom $\nu = n - 1$. The critical value G_C is obtained from statistical tables [66]. If the values m and ν fall between tabulated entries, G_C is determined using linear interpolation.

Once it has been established that the ranks of all criteria follow a normal distribution and that the rank variances σ_{Ri}^2 are homogeneous, the total variance of the ranks of all criteria for the entire object under investigation σ_R^2 can be calculated using Equation (15). This variance affects the accuracy of the research results, which is expressed as the marginal sampling error Δ_R and calculated based on the sample size using the modified Equation (19):

$$\Delta_R = \sqrt{\frac{t^2 \times \sigma_R^2}{n}} = \frac{t \times \sigma_R}{\sqrt{n}}. \quad (19)$$

Here, t is the critical value of Student's t -distribution corresponding to the selected confidence probability P and significance level α . For $P = 95\%$ (i.e., $\alpha = 0.05$), the value $t = 1.96$ is adopted [67]; and n denotes the number of experts who assessed the significance of the criteria.

3. Results and Discussion

3.1. Consistency of Expert Judgements

The significance of the criteria influencing the deployment of MMDs in the city of all experts is presented in Appendix A, where the sums of ranks $\sum_{e=1}^n R_{ie}$, skewness (Sk) and kurtosis (Ku) assigned to each i -th criterion are calculated. The mean ranks $\bar{R}_i$, standard deviations σ_{Ri} and the limits of interval $\bar{R}_i \pm \sigma_{Ri}$ outside of which R_{ie} values are considered outliers (Table 2), for each criterion were calculated using Equation (1).

Using the rank correlation method, Kendall's coefficient of concordance W was calculated according to Equation (2), based on the rankings of 15 criteria provided by 16 experts:

$$W = \frac{12S}{n^2(m^3 - m)} = \frac{12 \cdot 29074}{16^2(15^3 - 15)} = 0.4056$$

The deviation of the sums of criterion ranks $\sum_{e=1}^n R_{ie}$ from the overall mean rank $\bar{R} = \frac{n(m+1)}{2}$, expressed by the sum of squares S and calculated according to Equation (3), is presented in Table 2 and equals 29,074.

To assess the consistency of expert judgements, the chi-square statistic χ^2 , calculated according to Equation (4), was applied in the classical manner, as the number of evaluated criteria exceeds $m = 7$:

$$\chi^2 = Wn(m - 1) = 0.4056 \cdot 16(15 - 1) = 90.85.$$

For a significance level of $\alpha = 0.05$ and the corresponding number of degrees of freedom $\nu = m - 1 = 15 - 1 = 14$, the critical value of the chi-square statistic obtained from statistical tables [68] is $\chi_{0.05;14}^2 = 23.68$. The ratio of the empirical χ^2 value to the critical value $\chi_{0.05;14}^2$, calculated according to Equation (6) equals 3.84.

The minimum value of the coefficient of concordance $W_{\min}$, calculated according to Equation (5), enables direct comparison with the empirical value of W :

$$W_{\min} = \frac{\chi_{\alpha,\nu}^2}{n(m - 1)} = \frac{23.68}{16(15 - 1)} = 0.1057.$$

The results of the expert questionnaire show that the empirical value of the concordance coefficient, $W = 0.4056$, is 3.84 times greater than the minimum value $W_{\min} = 0.1057$. This allows a well-founded basis for concluding that the expert assessments of criterion significance are consistent (i.e., not contradictory). Consequently, the average ranks $\bar{R}_i$ can be regarded as reliable indicators of the average significance of the criteria influencing the deployment of MMDs in the city.

The standard deviation of ranks σ_{R_i} calculated for each criterion was used to determine the interval limits $\bar{R}_i \pm 3\sigma_{R_i}$, within which the rank values R_{ie} are considered acceptable, in accordance with the CIBRO method principle. Rank values falling outside these interval limits would be classified as outliers. In this study, the lower $\bar{R}_i - 3\sigma_{R_i}$ and upper $\bar{R}_i + 3\sigma_{R_i}$ threshold values defining the outlier intervals are presented in Table 2. The results indicate that the rank-based significance values of all criteria fall within the specified interval limits. Consequently, no outliers were identified, and all rank values R_{ie} provided by the experts were retained for further analysis.

3.2. Criterion Weights Calculated Using the ARTIW-L Method

The criterion weights $\omega_i^{\text{ARTIW-L}}$ calculated from the average ranks of each criterion $\bar{R}_i$ according to Equation (7) are presented in Table 2. The normalized relative weight of the first criterion (A) is

$$\omega_A^{\text{ARTIW-L}} = \frac{m + 1 - \hat{R}_A}{\sum_{i=1}^m \hat{R}_i} = \frac{15 + 1 - 6.188}{120} = 0.0818.$$

The relative weight of the most important criterion, B (travel time) $\omega_B^{\text{ARTIW-L}} = 0.1109$, is 3.4 times greater than that of the least important criterion, N (possibility of carrying multiple users), $\omega_N^{\text{ARTIW-L}} = 0.0323$. The relative weights of the remaining criteria fall within the interval defined by the maximum and minimum values, i.e., $0.1109 - 0.0323 = 0.0786$. The differences between the average relative weights of adjacent criteria are not uniform.

In contrast, the differences between the ranks R_{ie} assigned to adjacent criteria by an individual expert are equal and amount to one rank unit. Based on the relative weights calculated using the ARTIW-L method, the following priority order of criteria is obtained: $B \succ E \succ J \succ A \succ D \succ F \succ O \succ K \succ L \succ C \succ I \succ M \succ G \succ H \succ N$.

3.3. Criterion Weights Calculated Using the ARTIW-N Method

The significance of each criterion influencing the deployment of MMDs in the city was calculated from the average ranks $\bar{R}_i$ using the ARTIW-N method. The relative weight of each criterion $\omega_i^{\text{ARTIW-N}}$ (Table 2) was obtained using Equation (8) through a two-step procedure. First, the lowest average rank $\min_i \bar{R}_i = \bar{R}_B = 2.688$ was divided by the average rank of each i -th criterion $\bar{R}_i$ and the resulting ratio was denoted as u_i . For the first criterion, A (impact of MMDs on health), this ratio is

$$u_A = \frac{\min_i \bar{R}_i}{\bar{R}_i} = \frac{\bar{R}_B}{\bar{R}_A} = \frac{2.688}{6.188} = 0.4342.$$

Next, the value u_i for each criterion i , divided by the sum $\sum_{i=1}^m u_i = 6.1474$ of all u_i values, represents the normalized relative weight of the criterion obtained using the ARTIW-N method. The relative weight of the first criterion, A, is

$$\omega_A^{\text{ARTIW-N}} = \frac{u_A}{\sum_{i=1}^m u_i} = \frac{0.4342}{6.1474} = 0.0706.$$

The relative weight of travel duration $\omega_B^{\text{ARTIW-N}} = 0.1627$, identified by experts as the most important criterion (B), is 4.5 times greater than that of the least important criterion (N) $\omega_N^{\text{ARTIW-N}} = 0.0360$. The difference between the relative weights of these criteria, $0.1627 - 0.0360 = 0.1267$, is 1.6 times greater than the corresponding difference obtained using the ARTIW-L method (0.0786). The relative weights calculated using the ARTIW-N method yield the following priority order of criteria, $B \succ E \succ J \succ A \succ D \succ F \succ O \succ K \succ L \succ C \succ I \succ M \succ G \succ H \succ N$, which is identical to the priority order obtained using the ARTIW-L method.

3.4. Criterion Weights Calculated Using the DPW Method

The percentage weights P_{ie} assigned by all 16 experts to the 15 criteria are presented in Appendix B, where the corresponding standard deviations, skewness (Sk) and kurtosis (Ku) values are also calculated. Based on the significance values P_{ie} assigned by each expert to the criteria in the form of percentage weights, the normalized relative weights ω_i^{DPW} for all i -th criteria were calculated according to Equation (9). The mean relative weight of criterion A is provided in Table 2:

$$\omega_A^{\text{DPW}} = \frac{\sum_{e=1}^n P_{Ae}}{100 \cdot n} = \frac{138.24}{100 \cdot 16} = 0.0864.$$

The relative weight of the most important criterion, E (travel safety) $\omega_E^{\text{DPW}} = 0.1234$, is 3.5 times greater than that of the least important criterion N, which shows the possibility of carrying multiple users, relative weight $\omega_N^{\text{DPW}} = 0.0349$. The relative weight of criterion B $\omega_B^{\text{DPW}} = 0.1140$, calculated using this method, indicates that it ranks second in priority. Based on the relative weights obtained using the DPW method, the following priority order of criteria is established: $E \succ B \succ A \succ J \succ O \succ F \succ D \succ K \succ L \succ M \succ C \succ I \succ G \succ H \succ N$.

Table 2. Significance of 15 criteria influencing the deployment of micromobility devices, ranked by relative weights and priorities, calculated using four MCDM methods based on the judgements of a panel of 16 experts.

Calculation Method	Criterion $i = 1, 2, \dots, m$															Sum
	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	
$\sum_{e=1}^n R_{ie}$	99	43	145	106	44	118	172	182	157	94	136	142	160	194	123	1920
$\bar{R}_i = \sum_{e=1}^n R_{ie} / n$	6.188	2.688	9.062	6.625	2.750	7.357	10.750	11.688	9.812	5.875	8.500	8.875	10.000	12.125	7.687	120
Standard deviation of ranks σ_{Ri}	3.763	1.923	3.255	2.778	1.983	3.900	3.215	2.549	4.037	3.948	3.596	3.160	4.131	3.096	4.895	–
$\bar{R}_i - 3\sigma_{Ri}$	−5.1	−3.1	−0.7	−1.7	−3.2	−4.3	1.1	4.0	−2.3	−6.0	−2.3	−0.6	−2.4	2.8	−7.0	–
$\bar{R}_i + 3\sigma_{Ri}$	17.5	8.5	18.8	15.0	8.7	19.1	20.4	19.3	21.9	17.7	19.3	18.4	22.4	21.4	22.4	–
$\sum_{e=1}^n R_{ie} - \frac{n(m+1)}{2}$	−29	−85	17	−22	−84	−10	44	59	29	−34	8	14	32	66	−5	0
$\left[\sum_{e=1}^n R_{ie} - \frac{n(m+1)}{2} \right]^2$	841	7225	289	484	7056	100	1936	3481	841	1156	64	196	1024	4356	25	29,074
ARTIW-L method: $\omega_i^{\text{ARTIW-L}}$	0.0818	0.1109	0.0578	0.0781	0.1104	0.0719	0.0438	0.0359	0.0515	0.0844	0.0625	0.0594	0.0500	0.0323	0.0693	1
ARTIW-L priority	4	1	10	5	2	6	13	14	11	3	8	9	12	15	7	120
ARTIW-N method: $u_i = \frac{\min R_i}{R_i}$	0.4342	1	0.2965	0.4056	0.9771	0.3643	0.2499	0.2299	0.2738	0.4575	0.3161	0.3028	0.2687	0.2216	0.3495	6.1474
$\omega_i^{\text{ARTIW-N}}$	0.0706	0.1627	0.0482	0.0660	0.1589	0.0593	0.0407	0.0374	0.0445	0.0744	0.0514	0.0493	0.0437	0.0360	0.0569	1
ARTIW-N priority	4	1	10	5	2	6	13	14	11	3	8	9	12	15	7	120
DPW method: $\sum_{e=1}^n P_{ie}$	138.24	182.4	79.96	112.13	197.4	113.9	68.97	57.76	69.9	131.8	95.97	93.5	82.8	55.8	119.47	1600
ω_i^{DPW}	0.0864	0.1140	0.0500	0.0701	0.1234	0.0712	0.0431	0.0361	0.0437	0.0823	0.0600	0.0584	0.0517	0.0349	0.0747	1
DPW priority	3	2	11	7	1	6	13	14	12	4	8	9	10	15	5	120
AHP method: $\sum_{e=1}^n \omega_{ie}^{\text{AHP}}$	1.3307	2.1331	0.7831	1.1372	2.2648	1.1352	0.5729	0.4356	0.6671	1.5251	0.8945	0.7877	0.7053	0.4354	1.1930	16.0007
$\bar{\omega}_i^{\text{AHP}}$	0.0832	0.1333	0.0789	0.0711	0.1416	0.0710	0.0358	0.0272	0.0417	0.0953	0.0559	0.0492	0.0441	0.0272	0.0746	1.0001
AHP priority	4	2	10	6	1	7	13	14	12	3	8	9	11	15	5	120

3.5. Criterion Weights Calculated Using the AHP Method

Assessing the significance of 15 criteria for the deployment of MMDs in the city using the AHP method represents a demanding task for experts. Consequently, the consistency ratio (C.R.) of a completed pairwise comparison matrix $A = [a_{ij}]_{m \times m}$ does not always fall below the acceptable threshold of 0.1. If a matrix is inconsistent (C.R. > 0.1), it must be either revised or rejected. The matrix may be revised either by the expert (provided they are able to perform the correction) or by a skilled researcher, while preserving the priority order (ranks) originally assigned by the expert. In accordance with the transitivity condition, selected elements of the pairwise comparison matrix a_{ij} are adjusted, after which the consistency ratio (C.R.) is recalculated and typically reduced to a value below 0.1. A corrected matrix that satisfies this condition is considered acceptable, and its priority vector ω_{ie}^{AHP} , calculated according to Equation (10), is adopted as the relative weight assigned to the i -th criterion by the e -th expert.

The elements of the pairwise comparison matrix a_{ij} constructed by the first expert (E1), together with the corresponding priority vector ω_{ie} (relative weights) and the matrix consistency ratio (C.R. = 0.0262), are presented in Table 3. The left-hand side of the matrix displays the criterion ranks, while the bottom of the table shows the sequence of criteria ordered from the most important to the least important. This layout supports the expert in maintaining internal consistency during the pairwise comparison process.

Table 3. Pairwise comparison matrix of hierarchically unstructured criteria influencing the deployment of MMDs, assessed by the first expert (E1) using the AHP method, and the corresponding calculated relative weights ω_{iE1}^{AHP} .

Global Rank	Development of MMD	Criterion, $j = 1, 2, \dots, m$															Relative Weight ω_{iE1}^{AHP}	
		A	B	C	D	E	F	G	H	I	J	K	L	M	N	O		
3	Criterion, $i = 1, 2, \dots, m$	A	1	1	4	2	1	5	6	7	2	1	4	5	6	6	3	0.1375
1		B	1	1	4	2	1	5	6	9	3	2	4	5	7	8	3	0.1550
9		C	1/4	1/4	1	1/3	1/4	2	3	5	1/2	1/3	1	2	3	4	1/2	0.0444
5		D	1/2	1/2	3	1	1/2	4	5	7	1	1	3	4	5	6	2	0.0969
2		E	1	1	4	2	1	5	6	8	3	2	4	5	6	7	3	0.1509
10		F	1/5	1/5	1/2	1/4	1/5	1	2	5	1/3	1/4	1/2	2	3	4	1/3	0.0328
12		G	1/6	1/6	1/3	1/5	1/6	1/2	1	3	1/4	1/5	1/4	1	1	2	1/4	0.0205
15		H	1/7	1/9	1/5	1/7	1/8	1/5	1/3	1	1/6	1/7	1/5	1/4	1/2	1	1/5	0.0114
6		I	1/2	1/3	2	1	1/3	3	4	6	1	1/2	2	3	4	5	1	0.0724
4		J	1	1/2	3	1	1/2	4	5	7	2	1	3	4	5	6	2	0.1063
8		K	1/4	1/4	1	1/3	1/4	2	4	5	1/2	1/3	1	3	4	5	1/2	0.0481
11		L	1/5	1/5	1/2	1/4	1/5	1/2	1	4	1/3	1/4	1/3	1	2	3	1/3	0.0261
13		M	1/6	1/7	1/3	1/5	1/6	1/3	1	2	1/4	1/5	1/4	1/2	1	1	1/4	0.0175
14		N	1/6	1/8	1/4	1/6	1/4	1/4	1/2	1	1/5	1/6	1/5	1/3	1	1	1/5	0.037
7		O	1/3	1/3	2	1/2	1/3	3	4	5	1	1/2	2	3	4	5	1	0.0665
Sequence		B > E > A > J > D > I > O > K > C > F > L > G > M > N > H. C.R. = 0.0262															Σ1.0000	

The relative weights ω_{ie}^{AHP} of all criteria, the consistency ratios (C.R.), standard deviations σ_{ω_i} , skewness coefficients (Sk), and kurtosis coefficients (Ku) are presented in Appendix C. The averages of the relative weights $\bar{\omega}_i^{AHP}$, calculated according to Equation (13), are presented in Table 2. The average relative weight of the first criterion (A), calculated using the AHP method based on the assessments of 16 experts, is

$$\bar{\omega}_A^{AHP} = \frac{\sum_{e=1}^n \omega_{Ae}^{AHP}}{n} = \frac{1.3307}{16} = 0.0832.$$

The relative weight of the most significant criterion, E $\bar{\omega}_E^{AHP} = 0.1416$, is 5.2 times greater than that of the least significant criterion, N $\bar{\omega}_N^{AHP} = 0.0272$. The relative weight of the second most important criterion, B, is $\bar{\omega}_B^{AHP} = 0.1333$. The average relative weights

of the criteria calculated using the AHP method indicate the following priority order: $E > B > J > A > O > D > F > K > L > C > M > I > G > H > N$.

3.6. Correlation Between Relative Weights and Average Criterion Ranks

The correlation between the relative weights ω_i of the criteria calculated using different MCDM methods and the average ranks $\bar{R}_i$ of these criteria is illustrated in Figure 1. The relative weights of the criteria ($\omega_i^{\text{ARTIW-L}}$ and $\omega_i^{\text{ARTIW-N}}$) obtained from the average ranks $\bar{R}_i$ using the ARTIW-L and ARTIW-N methods are functionally related to the average ranks, with a coefficient of determination $R^2 = 1$ (Figure 1a,b). The ARTIW-N method assigns higher relative weights to the most important criteria (B and E) while assigning lower relative weights to criteria of moderate importance.

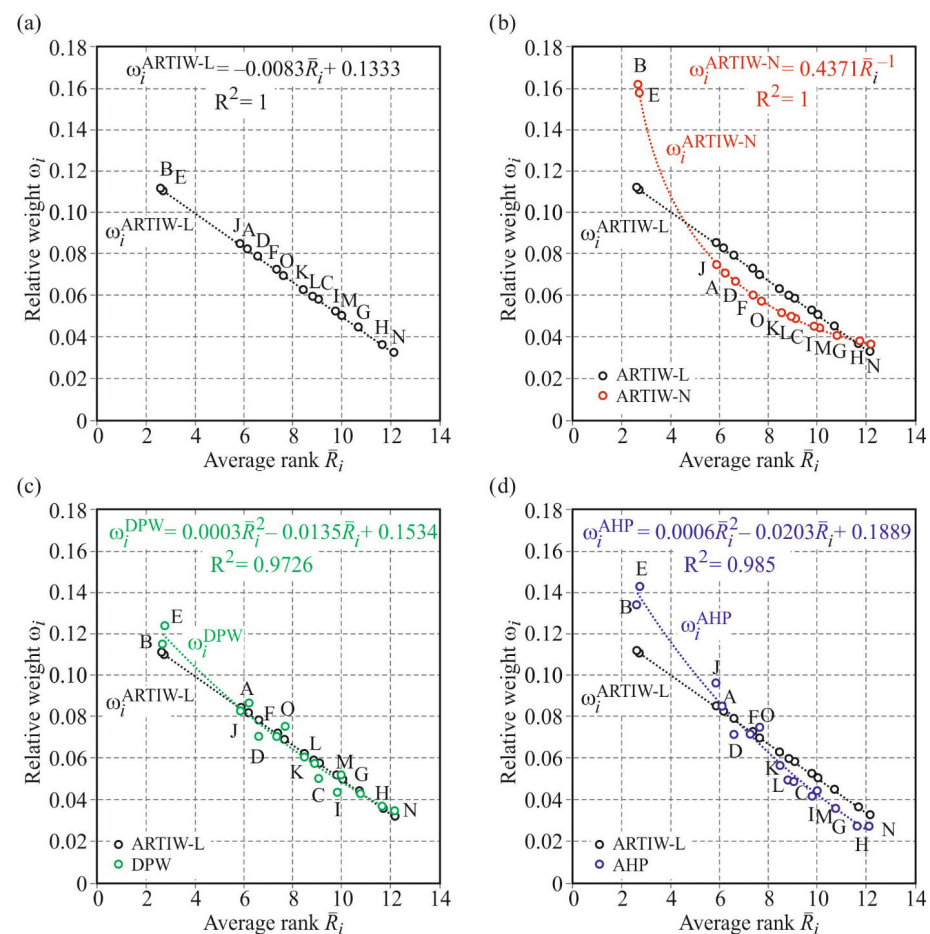


Figure 1. Correlation between the relative weights of MMD criteria calculated using different MCDM methods and the average ranks of these criteria: (a) ARTIW-L; (b) ARTIW-N; (c) DPW; (d) AHP.

The relative weights of criteria (ω_i^{DPW} and ω_i^{AHP}) calculated using the DPW and AHP methods and their relationship with the average criterion ranks $\bar{R}_i$ exhibit inverse curvilinear correlations, with coefficients of determination $R^2 = 0.9726$ and $R^2 = 0.985$, respectively (Figure 1c,d). This close functional relationship is well described by a quadratic regression model: $y = a_0 + ax + bx^2$. The relative weights of criteria ω_i^{DPW} and $\omega_i^{\text{ARTIW-L}}$ calculated using the DPW method are most similar to those obtained using the ARTIW-L method (Figure 1c). In contrast, application of the AHP method assigns higher relative weights ω_i^{AHP} for the most important criteria (B and E), while reducing the relative weights of the least significant criteria (N, H, G, and I) (Figure 1d). These regression models derived

in this research enable systematic comparison of the results obtained using different MCDM methods and facilitate prediction of numerical estimates of criterion significance.

As can be seen, each applied method yields different results for criterion weights; therefore, there is no theoretical justification for considering any single MCDM method superior to others. For this reason, the average of the results obtained from four methods, as applied in this study, is considered the most reliable solution to the problem. Figure 1 presents a comparison in which the ARTIW-L (linear) method is used as the reference point. As can be observed, significant differences are obtained when comparing criteria B and E; however, the trends in the variation in relative weights remain consistent.

3.7. Average Criterion Weights Obtained Using Four MCDM Methods

In practice, no benchmark exists against which the results obtained using individual MCDM methods can be directly compared. Therefore, the significance of each criterion i was determined according to Equation (14) by calculating the average relative weight ω_i across all MCDM methods applied in the current research. The final relative weight of the first criterion (A) is

$$\omega_A = \frac{\sum_{k=1}^r \omega_{Ak}}{r} = \frac{0.0818 + 0.0706 + 0.0864 + 0.0832}{4} = 0.0805.$$

The final relative weights ω_i calculated for all criteria, along with the resulting priority order, are presented in Figure 2. Among all criteria, travel safety (E) and travel time (B) are identified as the most important, with relative weights of 0.1336 and 0.1302, respectively.

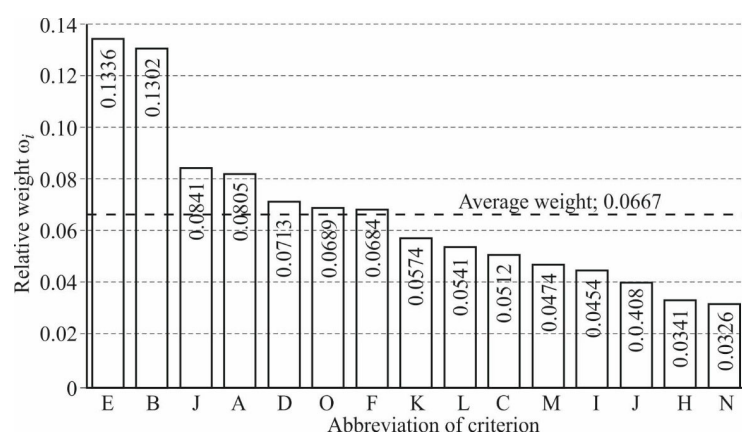


Figure 2. Priority sequence of criteria influencing the deployment of micromobility devices, determined based on the average relative weights calculated using four MCDM methods.

The relative weight ω_i of a criterion, calculated by averaging the results obtained using four MCDM methods applied in this research, is considered more reliable than a relative weight derived using any single method. The current research assumes that none of the applied methods has a theoretical advantage (dominance) over the others.

The relative weights of all criteria, indicating how many times one criterion is more important than another, are presented in Table 4. In this table, all 15 criteria are arranged from the most important criterion, E, to the least important criterion, N. The ordering is shown along the left-hand column from bottom to top, along the top row from left to right. The results show that travel safety is 4.1 times more important than the possibility of carrying multiple users by an MMD.

Table 4. Ratios of pairwise comparison of the relative weights of criteria influencing the deployment of micromobility devices in cities.

Quality of MMD		Criterion, $j = 1, 2, \dots, m$														
		E	B	J	A	D	O	F	K	L	C	M	I	G	H	N
Criterion $i = 1, 2, \dots, m$	E	1	1.03	1.59	1.66	1.87	1.94	1.9	2.33	2.47	2.61	2.82	2.94	3.27	3.92	4.10
	B		1	1.55	1.62	1.83	1.89	1.90	2.27	2.41	2.54	2.75	2.87	3.19	3.82	3.99
	J			1	1.04	1.18	1.22	1.23	1.47	1.55	1.64	1.77	1.85	2.06	2.47	2.58
	A				1	1.13	1.17	1.18	1.40	1.49	1.57	1.70	1.77	1.97	2.36	2.50
	D					1	1.03	1.04	1.24	1.32	1.39	1.50	1.57	1.75	2.09	2.19
	O						1	1.01	1.20	1.27	1.35	1.45	1.52	1.69	2.02	2.11
	F							1	1.19	1.26	1.34	1.44	1.51	1.68	2.01	2.10
	K								1	1.06	1.12	1.21	1.26	1.41	1.68	1.76
	L									1	1.06	1.14	1.19	1.33	1.59	1.66
	C										1	1.08	1.13	1.25	1.50	1.57
	M											1	1.04	1.16	1.93	1.45
	I												1	1.11	1.33	1.39
	G													1	1.20	1.25
	H														1	1.05
	N															1

3.8. Sample Size and Result Accuracy

The conformity of the criterion ranks R_{ie} to a normal distribution was assessed by comparing the absolute values of the empirical skewness $|Sk|$ and kurtosis $|Ku|$ coefficients for each criterion with their corresponding standard deviations s_{Sk} and s_{Ku} , calculated according to Equations (16) and (17). The values of s_{Sk} and s_{Ku} , which depend solely on the sample size n (i.e., the number of experts in the panel), are equal to 0.564 and 1.091, respectively, for $n = 16$. The obtained skewness $3s_{Sk} = 1.693$ and kurtosis $5s_{Ku} = 5.454$ values for each criterion do not exceed the corresponding $|Sk|$ and $|Ku|$ threshold values, indicating that the criterion ranks conform to a normal distribution. The results (Appendix A) confirm that, for all 15 criteria, the absolute values of skewness $|Sk|$ and kurtosis $|Ku|$ remain below the respective thresholds, thereby validating the assumption of normality for the rank distributions.

The homogeneity of rank variances, calculated from samples of equal size and assumed to follow a normal distribution, was assessed using Cochran's test $\hat{G}_{\max}$, calculated according to Equation (18):

$$\hat{G}_{\max} = \frac{\max_i \sigma_{Ri}^2}{\sum_{i=1}^m \sigma_{Ri}^2} = \frac{23.96}{177.295} = 0.1351.$$

The critical tabulated value of the Cochran's test statistic, $G_C(\alpha; m; \nu) = (0.05; 15, 15) = 0.1469$ [66], was obtained by linear interpolation between the values 0.1429 (for $\nu = 16$) and 0.1671 (for $\nu = 10$). Therefore, it can be concluded that the variances of the ranks σ_{Ri}^2 of all 15 criteria are statistically equal.

Accordingly, the average variance of the ranks σ_{Ri}^2 for all criteria was calculated using Equation (15):

$$\sigma_R^2 = \frac{\sum_{i=1}^m \sigma_{Ri}^2}{m} = \frac{177.295}{15} = 11.82.$$

The corresponding standard deviation of the ranks across all criteria is $\sigma_R = 3.44$.

The accuracy of the research results was determined using Equation (19) by calculating the marginal sampling error Δ_R , assuming a significance level of $\alpha = 0.05$, a Student's t -distribution value of $t = 1.96$, and a sample size of $n = 16$:

$$\Delta_R = \sqrt{\frac{t^2 \times \sigma_R^2}{n}} = \sqrt{\frac{1.96^2 \times 3.44^2}{16}} = 1.68.$$

The calculated margin of error, $\Delta_R = 1.68$, shows that the average rank $\bar{R}_i$ of any criterion in the population lies within the interval $\bar{R}_i - 1.68, \bar{R}_i + 1.68$ with a confidence level of 95%. Increasing the number of experts n narrows this interval, as the value of Δ_R decreases. For example, assuming the same rank variance $\sigma_R^2 = 11.82$ and $t = 1.96$, increasing the sample size to $n = 30$ reduces the margin of error to $\Delta_R = 1.23$. Further increasing the number of experts to 50 results in a margin of error of 0.95.

The following conclusions are drawn from the results of the research and their analysis.

4. Conclusions

The deployment of micromobility devices (MMDs) contributes significantly to the improvement of road transport performance indicators in urban areas. However, this deployment is influenced by a set of criteria whose significance has so far been insufficiently investigated and, consequently, has not been quantitatively assessed. Expert-based research methods are therefore appropriate for determining the significance of these criteria, as they enable the competence, knowledge, and experience of specialists (experts) to be used to quantitatively evaluate systematized criteria by comparing them either pairwise or collectively. Each expert independently assesses the significance of the criteria using ranks, percentage weights, and intensity values derived from AHP pairwise comparison matrices, while the researcher subsequently processes these assessments using appropriate multi-criteria decision-making (MCDM) methods.

The current research systematizes 15 criteria influencing the deployment of MMDs, the significance of which was assessed by a panel of 16 highly qualified experts. Statistical analysis revealed that no rank outliers were identified and that expert judgements are aligned, as the coefficient of concordance 0.405 is 3.8 times greater than the minimum threshold value 0.106. This justified the use of arithmetic mean ranks as quantitative estimates of criterion significance, despite certain differences and variability in the assessments provided by individual experts.

The relative weights of criteria were calculated from the average ranks using the ARTIW-L and ARTIW-N methods, while percentage weights were applied to determine criterion weights using the DPW method. In addition, criterion significance was assessed using the AHP method by calculating the priority vectors of the criteria and the consistency ratios of all 16 pairwise comparison matrices, all of which were below the accepted threshold of 0.1. The criterion weights obtained using the four MCDM methods differ only slightly, and the resulting priority orders of the criteria are nearly identical. Consequently, the arithmetic mean of the relative weights calculated for each criterion using the four methods was adopted as the final solution. According to the expert assessments, the most important criteria influencing the deployment of MMDs are travel safety (0.1336), travel time (0.1302), the influence of infrastructure quality on comfort (0.0841), impact on health (0.0805), and the cost of purchasing an MMD (0.0713), while the remaining ten criteria are of lower significance. Notably, the relative weight of the most significant criterion, E (travel safety), is 4.1 times greater than that of the least significant criterion N (possibility of carrying multiple users). The prioritization of travel safety (0.1336) and travel time (0.1302) aligns with the literature, which identifies these factors as key determinants of user adoption and system efficiency [20,69,70]. However, this research extends previous studies by quantitatively demonstrating that travel safety is 4.1 times more significant than the least important criterion, providing a clearer basis for policy and infrastructure planning decisions.

In addition, based on the obtained results, strategies for urban infrastructure and resident mobility development can be formulated, taking into account travel safety and duration criteria. Politically independent experts assessed these criteria as exceptionally significant, and thus they cannot be ignored when making policy decisions regarding the expansion of micromobility solutions in cities. The results are applicable to medium- and large-sized cities where micromobility options are insufficiently available and where urban infrastructure developers allocate inadequate investments for planning and implementing such solutions.

The ranks of all criteria follow a normal distribution, as the absolute values of the empirical skewness and kurtosis are lower than the corresponding threshold values, calculated as three times the standard deviation of skewness and five times the standard deviation of kurtosis, respectively. This allowed Cochran's test to be applied to calculate the test statistic $\hat{G}_{\max}$ and compare it with the corresponding critical value $G_C(\alpha; m; v)$. The calculated value $\hat{G}_{\max} = 0.1351$ is lower than the critical value $G_C(0.05; 15; 15) = 0.1469$, indicating that the variances of the ranks are statistically equal and that the mean value can be considered a valid measure of variability in the significance of all criteria. The accuracy of the study results, calculated using the sample size-based equation, is equal to 1.68. When the criteria influencing the deployment of MMDs were evaluated by 16 experts with a 95% confidence level (significance level of 0.05), the mean variance of ranks across all criteria was 11.82.

The originality of this research is demonstrated by the integrated application of the selected methods and the identification of results that are highly relevant to contemporary society. It should be noted that the experts involved in the study are from the same region; therefore, the findings can be effectively applied to urbanized areas of a similar nature. Results are based on expert judgment rather than empirical operational data; therefore in future research it is planned to use real flow data already collected within cycling infrastructure, as well as to conduct a dedicated survey of urban residents using micromobility solutions and integrate these findings into the overall research framework.

In addition, in future research, five MMD alternatives will be compared based on the 15 identified criteria, their priorities will be determined, and the most suitable overall MMD will be identified. Future research is also planned to examine the sensitivity of the ranking of criteria to changes in criterion weights or stakeholder assumptions, i.e., to conduct a sensitivity analysis by applying alternative approaches to calculating the weighted average of expert evaluations.

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Appendix A

Table A1. Rank-based significance of hierarchically unstructured quality criteria influencing the deployment of micromobility devices (MMDs).

Expert <i>e</i> = 1, 2, . . . , <i>n</i>	Quality Criterion <i>i</i> = 1, 2, . . . , <i>m</i>														
	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O
E1	3	1	9	5	2	10	12	15	6	4	8	11	13	14	7
E2	4	1	5	9	2	8	14	12	7	3	11	10	13	15	6
E3	4	3	8	9	2	12	15	10	6	1	5	7	13	14	11
E4	11	5	15	3	6	9	10	12	14	1	4	7	2	13	8
E5	5	2	11	7	1	15	12	13	6	9	2	4	8	10	14
E6	14	3	15	4	2	8	11	9	12	1	5	10	6	13	7
E7	2	5	9	10	1	4	15	6	7	8	11	13	12	14	3
E8	3	2	4	5	1	6	7	8	9	11	10	12	14	13	15
E9	8	3	7	11	5	2	9	13	15	4	14	6	12	10	1
E10	2	3	6	7	1	9	11	12	5	4	8	14	13	15	10
E11	10	1	12	3	4	11	13	15	8	7	5	6	9	14	2
E12	3	1	6	8	2	10	11	14	15	5	12	13	4	7	9
E13	3	1	7	6	2	4	9	13	5	12	8	10	15	11	14
E14	9	2	11	4	7	6	13	10	15	3	14	8	5	12	1
E15	9	8	10	11	5	1	3	14	15	13	12	6	7	4	2
E16	9	2	10	4	1	3	7	11	12	8	6	5	14	15	13
Total	99	43	145	106	44	118	172	187	157	94	136	142	160	194	123
Skewness	0.60	1.60	0.41	0.27	1.04	0.07	−0.84	−0.73	0.25	0.45	0.08	0.14	−0.62	−1.52	0.01
Kurtosis	−0.85	2.82	−0.39	−1.31	−0.23	−0.58	0.81	0.085	−1.80	−0.97	−1.31	−1.30	−1.02	2.09	−1.35

Appendix B

Table A2. Significance of hierarchically unstructured quality criteria influencing the deployment of micromobility devices (MMDs), expressed as percentage weights.

Expert $e = 1, 2, \dots, n$	Quality Criterion $i = 1, 2, \dots, m$														
	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O
E1	8.5	11	6	7.9	9.5	5.6	5	3.8	7.7	8	6.2	5.3	4.5	4	7
E2	9.6	14.2	7.6	5.4	13.1	6.1	2.1	3.1	6.90	11.7	3.8	4.6	2.8	1.7	7.3
E3	8.5	12	5	4.5	15	3	1	4	6	20	7.5	5.5	2.5	2	3.5
E4	4.2	9.2	0.8	10.8	8.3	5.8	5	3.3	1.7	12.5	10	7.5	11.7	2.5	6.7
E5	8	15	3	5	20	1	2.5	2	6	4	13	11	4.5	3.5	1.5
E6	1.7	10.8	0.8	10	11.7	6.7	4.2	5.8	3.3	12.5	9.7	5	8.3	2.5	7.5
E7	20	5	3	2.9	21.7	10	1	4	3.9	3.5	2.8	2.5	2.7	2	15
E8	10.5	11.5	9	8.5	13	7	6.5	6	5.5	4.5	5	4	3	3.5	2.5
E9	6.7	10.2	7.1	5.1	8.6	11	6	3	0.9	9	1.3	7.9	4.3	5.7	13.2
E10	10.1	9	7.6	7	11	6.2	5.2	4.7	8	8.6	6.7	3.2	4	2.9	5.8
E11	5.5	12	4.5	9	8.5	5	4	3	6.5	7	8	7.5	6	3.5	10
E12	15	17	6	5	16	4	3.5	2	1	6.5	3	2.5	8.5	5.5	4.5
E13	13	15	6	6.5	14	9	5	3	7	4	5.5	4.5	1.5	3.5	2.5
E14	5.5	13	3	10	7	8	1.5	3.5	1	11	2	6	9	2.5	17
E15	6	6.5	5.5	5	8	15	9	2	0.5	3	4	7.5	7	8.5	12.5
E16	5.5	11	5	9.5	12	10.5	7.5	4.5	4	6	8	6	2.5	2	3
Total	138.24	182.4	79.96	112.13	197.4	113.9	68.97	57.76	69.9	113.8	92.97	93.5	82.8	55.8	119.47
Mean	8.64	11.40	5.00	7.01	12.34	7.12	4.31	3.61	4.37	8.23	6.00	5.84	5.17	3.49	7.47
Standard deviation	4.504	3.122	2.369	2.415	4.267	3.424	2.321	1.217	2.673	4.505	3.196	2.398	2.935	1.778	4.798
Skewness	1.06	−0.28	−0.33	0.09	0.89	0.51	0.25	0.56	−0.23	1.14	0.49	0.48	0.83	1.71	0.68
Kurtosis	1.56	0.17	−0.48	−1.29	0.28	0.72	−0.42	−0.09	−1.56	1.65	−0.11	−0.20	−0.21	3.26	−0.61

Appendix C

Table A3. Significance of hierarchically unstructured quality criteria influencing the deployment of micromobility devices (MMDs), determined using the AHP method.

Expert $e = 1, 2, \dots, n$	Quality Criterion $i = 1, 2, \dots, m$															C.R.
	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	
E1	0.1375	0.1550	0.0444	0.0969	0.1509	0.0328	0.0205	0.0114	0.0724	0.1063	0.0481	0.0261	0.0175	0.0137	0.0665	0.0262
E2	0.1024	0.1789	0.0845	0.0403	0.1476	0.0522	0.0164	0.0237	0.0600	0.1262	0.0281	0.0397	0.0193	0.0116	0.0722	0.0161
E3	0.1043	0.1337	0.0450	0.0423	0.1481	0.0203	0.0116	0.0308	0.0671	0.1815	0.0948	0.0640	0.0150	0.0148	0.0268	0.0299
E4	0.0270	0.0818	0.0116	0.146	0.0712	0.0409	0.0325	0.0223	0.0157	0.2062	0.1065	0.0542	0.1456	0.0219	0.0481	0.0466
E5	0.0617	0.1579	0.0260	0.0640	0.2622	0.0207	0.0258	0.0243	0.0415	0.0302	0.1250	0.1052	0.0337	0.0280	0.0238	0.0225
E6	0.0136	0.1274	0.0106	0.1075	0.1419	0.0443	0.0247	0.0377	0.0200	0.1968	0.0980	0.0293	0.0719	0.0181	0.0584	0.0391
E7	0.1700	0.0722	0.0352	0.0301	0.1908	0.1132	0.0131	0.0690	0.0511	0.0435	0.0268	0.0177	0.0196	0.0153	0.1324	0.0219
E8	0.1069	0.1545	0.1069	0.0948	0.1618	0.0782	0.0671	0.0518	0.0413	0.0292	0.0338	0.0240	0.0171	0.0199	0.0127	0.0236
E9	0.0480	0.1212	0.0608	0.0285	0.0887	0.1592	0.0399	0.0149	0.0089	0.1088	0.0113	0.0654	0.0204	0.0354	0.1886	0.0297
E10	0.1350	0.1249	0.0823	0.0549	0.1761	0.0450	0.0275	0.0231	0.0844	0.1189	0.0478	0.0134	0.0179	0.0112	0.0378	0.0390
E11	0.0396	0.1661	0.0259	0.1198	0.1122	0.0290	0.0181	0.0128	0.0542	0.0670	0.0813	0.0776	0.0439	0.01530	0.1397	0.0223
E12	0.1393	0.1459	0.0906	0.0589	0.1447	0.0356	0.0277	0.0152	0.0119	0.0920	0.0220	0.0197	0.0941	0.0616	0.0408	0.0218
E13	0.1141	0.1674	0.0624	0.0716	0.1408	0.0923	0.0473	0.0227	0.0910	0.0291	0.0558	0.0357	0.0169	0.0332	0.0198	0.0115
E14	0.0487	0.1489	0.0261	0.1079	0.0674	0.0794	0.0115	0.0310	0.0102	0.1158	0.0146	0.0549	0.0955	0.0190	0.1650	0.0292
E15	0.0427	0.0553	0.0359	0.0296	0.0857	0.1751	0.1224	0.0157	0.0137	0.0226	0.0241	0.0693	0.0623	0.1039	0.1418	0.0141
E16	0.0426	0.142	0.0349	0.1055	0.1747	0.117	0.0628	0.0292	0.0237	0.051	0.0765	0.0945	0.0146	0.0125	0.0186	0.0168
Mean	0.0832	0.1333	0.0489	0.0711	0.1416	0.0710	0.0358	0.0272	0.0417	0.09530	0.0559	0.0492	0.0441	0.0272	0.0746	1.0000
Standard deviation	0.048	0.036	0.029	0.035	0.050	0.048	0.028	0.015	0.028	0.061	0.036	0.028	0.039	0.024	0.059	
Skewness	0.24	−1.06	0.61	0.07	0.53	1.00	2.13	1.66	0.36	0.54	0.52	0.55	1.48	1.56	0.78	
Kurtosis	−1.31	0.36	−0.68	−1.83	1.08	0.03	5.21	3.02	−1.23	−0.78	−1.06	−0.71	1.57	6.94	−0.89	

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