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Multi-criteria Prioritization of Shared Mobility Hub Locations: An Integrated BWM-TOPSIS Approach

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Abstract

Strategic investment in shared mobility infrastructure necessitates balancing multiple conflicting criteria. This study develops and applies an integrated Best-Worst Method (BWM) and Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) framework to prioritize urban zones for shared mobility hub investment in Budapest, Hungary. Vector normalization was adopted in the TOPSIS stage for its scale-invariance properties, ensuring robust cross-criteria comparability. The methodology incorporates 17 sub-criteria across five main dimensions: Transport Connectivity, Demand Density, Infrastructure Readiness, Environmental Impact, and Social Equity. Expert judgments were synthesized using BWM and applied to evaluate four distinct urban typologies: the Historic Central Business District (Zone A), Mixed-Use Residential Corridor (Zone B), Major Transport Hub & University Area (Zone C), and Residential Suburb (Zone D).

Results identify Zone B (Újlipótváros - Angyalföld) as the top priority, offering the best balance between high demand and implementation feasibility. Zone A (Belváros - Lipótváros), the historic CBD, ranks second, as its superior connectivity is offset by severe spatial constraints. Zone C (Kelenföld - Albertfalva), a major transport hub, places third, while Zone D (Péterhegy - Kőbánya), a residential suburb, ranks fourth due to lower current connectivity despite strong environmental and social equity scores.

The analysis reveals a core planning trade-off: zones with the highest immediate demand face the greatest physical implementation challenges. The proposed framework provides municipal planners with a transparent, quantitative tool for optimizing phased infrastructure investment, with future work recommended to incorporate real-time and time-dependent mobility data for dynamic scenario analysis.

Keywords

shared mobility, urban planning, multi-criteria decision making (MCDM), Best-Worst Method (BWM), TOPSIS, sustainable mobility investment

1 Introduction

Rapid urbanization has intensified classic municipal challenges: traffic congestion degrades mobility, vehicle emissions impair public health, and competition for scarce public space escalates [1], [2]. In this context, shared mobility systems—encompassing e-scooters, e-bikes, and car-sharing—have emerged as a promising component of sustainable urban transport strategies [3], [4]. By promoting a shift from private vehicle ownership to usership, these systems can potentially reduce the number of vehicles on the road, lower greenhouse gas emissions, and decrease demand for parking infrastructure [5], [6]. For civil engineers and urban planners, however, realizing this potential presents a distinct infrastructural challenge. The effective operation of shared mobility relies not just on the vehicles themselves, but on the supporting physical infrastructure: dedicated parking and docking stations, charging points, and designated lanes, all of which require careful integration into the built environment [7].

While the benefits of shared mobility are widely discussed, a critical civil engineering planning gap remains. Municipal authorities and transport engineers face a complex, resource-constrained decision: Where should limited public investment in physical shared mobility infrastructure be prioritized first? This is not merely a question of identifying high-demand areas. It involves navigating a web of conflicting criteria, including technical feasibility (e.g., space availability, utility access), economic viability (projected demand and cost), environmental impact (potential for

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emission reduction), and social equity (improving access for underserved communities) [8], [9]. The absence of a structured, transparent decision-support framework often leads to ad-hoc planning, potentially misallocating capital and undermining system efficacy and fairness [10].

Multi-Criteria Decision-Making (MCDM) methods are uniquely suited to address this complex, multi-faceted problem. They provide a systematic methodology to evaluate alternatives against a set of conflicting criteria, incorporating both quantitative data and qualitative expert judgment [11], [12]. This is essential for civil engineering projects that must satisfy diverse stakeholder objectives—from technical performance and cost-effectiveness to broader sustainability and social goals [13]. Among MCDM techniques, the Best-Worst Method (BWM) offers advantages in deriving reliable criterion weights with reduced comparison complexity and higher consistency [14], while the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) provides a robust mechanism for ranking alternatives based on their relative distance from ideal benchmarks [15].

The primary aim of this paper is to bridge the identified planning gap by developing and demonstrating an integrated BWM-TOPSIS framework tailored for prioritizing urban zones for shared mobility hub investment. The novelty of this work lies in its pragmatic focus on zonal prioritization for master planning, rather than micro-level site selection, making it an accessible and scalable tool for city-wide strategic planning. The framework is operationalized through a hierarchy of 17 sub-criteria spanning five key dimensions relevant to civil engineering practice. We demonstrate its application through a case study of Budapest, Hungary, evaluating four distinct urban typologies to derive a clear, justified investment sequence.

The remainder of this paper is structured as follows: Section 2 reviews relevant literature on shared mobility infrastructure and MCDM applications in transport planning. Section 3 details the proposed BWM-TOPSIS methodology and the criteria hierarchy, also provides a concise explanation of the zone delineation process, including the administrative and functional considerations that guided the selection of the four urban typologies. Section 4 presents the Budapest case study, including zone descriptions and data collection. Also, it reports the results, including criterion weights, zone rankings, and sensitivity analysis. Section 5 discusses the practical implications, limitations, and policy recommendations. Finally, Section 6 concludes by summarizing key findings and suggesting directions for future research.

2 Literature review

2.1 Shared mobility and urban infrastructure: From service model to physical integration

The scholarly discourse on shared mobility has progressed through distinct phases, beginning with conceptual exploration of business models and user adoption patterns [16]. Early optimism about shared mobility's potential to reduce private vehicle ownership and associated congestion and emissions has matured into a more nuanced understanding of its integration challenges within existing urban fabric [17], [18]. A critical evolution in this literature is the recognition that shared mobility's efficacy depends not merely on digital platforms and vehicle availability, but fundamentally on engineered physical infrastructure that must be strategically embedded within the public realm [19].

A recent systematic review by Chen et al. [20] identifies four emerging themes in shared mobility research: attitude and intention, cooperation behaviours, operations and decisions, and performance evaluation. Notably, the authors find that how shared mobility applications improve sustainability and impact various stakeholders remains unclear, positioning "performance evaluation" as an underdeveloped but critical research direction.

This infrastructural imperative manifests across multiple dimensions. First, parking and docking infrastructure represents a primary civil engineering concern. The proliferation of free-floating e-scooter and bike systems has highlighted acute "curb management" challenges, where vehicles clutter sidewalks, creating accessibility and safety hazards [21], [22]. Research by Butler et al. [23] demonstrates that the lack of designated parking significantly increases operational costs (through rebalancing) and reduces public acceptance. For station-based car-sharing, studies by Millard-Ball et al. [24] show that the strategic placement and quantity of dedicated, publicly allocated parking bays are critical determinants of system reliability and vehicle utilization rates, directly linking municipal land-use policy to service performance.

Second, charging infrastructure introduces electrical and spatial demands. The electrification of shared fleets (e-scooters, e-bikes, cars) necessitates a distributed network of charging stations or battery swap points. This requires coordination with electrical grid capacity, utility access points, and urban design to house charging hardware, presenting a non-trivial civil engineering problem intersecting energy and transportation systems [25].

Third, the safe operation of shared micromobility necessitates dedicated lane infrastructure. Research by

Sievert et al. [26] indicates that user safety perception and actual accident rates are strongly tied to the availability of protected bike lanes. Thus, investments in shared mobility cannot be decoupled from broader street redesign projects—a core domain of highway and transport engineering—that reallocate road space from general traffic to protected active transport corridors [27].

Recent conceptual work by Geurs et al. introduces the "Smarthubs Integration Ladder," a framework identifying three critical dimensions for shared mobility hub success: physical integration (infrastructure and location), digital integration (data and payment systems), and democratic integration (community participation and governance) [28]. Their review of existing hub implementations finds that digital and democratic dimensions are typically missing in current planning practice, implying that even well-designed physical infrastructure "will not reach its full potential in terms of user and societal value" if these broader integration aspects are neglected [28]. This finding underscores that shared mobility infrastructure planning must be inherently multi-dimensional, incorporating technical, social, and governance considerations simultaneously.

Collectively, this body of work establishes that shared mobility is not a purely digital or logistical service but a socio-technical system anchored in physical civil infrastructure. Its successful deployment requires deliberate planning around space allocation, structural supports, utility integration, and traffic engineering—all squarely within the traditional purview of civil engineering. However, current literature often treats these infrastructure needs reactively or descriptively, lacking a proactive, systematic framework for prioritizing where such finite infrastructure investments should be made first within a city.

2.2 MCDM in civil engineering and transport planning: Methods and evolution

Multi-Criteria Decision-Making (MCDM) provides a robust, structured philosophy for evaluating alternatives against multiple, often conflicting objectives, making it indispensable in complex civil engineering and planning contexts where technical, economic, environmental, and social considerations intersect [11]. Its application in transport planning and infrastructure development is extensive and methodologically diverse.

The Analytic Hierarchy Process (AHP), pioneered by Saaty [29], has been a cornerstone for its ability to decompose complex problems into a hierarchy of criteria, sub-criteria, and alternatives. In transport, AHP has been successfully applied to problems such as optimal site selection for intermodal terminals, prioritization of highway corridor improvements, and evaluation of public transport system alternatives [30], [31]. Its strength lies in facilitating structured expert judgment, but it is often critiqued for potential inconsistencies in pairwise comparison matrices, especially as the number of criteria increases, and for the cognitive burden placed on experts who must evaluate $n(n-1)/2$ comparisons [32], [33].

The Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), developed by Hwang and Yoon [34], offers a compensatory model based on the intuitive geometric concept of distance. An alternative is considered superior if it has the shortest Euclidean distance from a hypothetical "ideal" solution (which excels in all criteria) and the farthest distance from a "negative-ideal" solution. TOPSIS is prized for its computational simplicity, clear logic, and ability to incorporate both quantitative and qualitative data. It has been widely used in civil engineering for contractor selection, material selection, and sustainable transport project appraisal [35], [36]. Other prominent MCDM methods include PROMETHEE (outranking methods) and VIKOR (compromise ranking), each with specific strengths in handling uncertainty and non-commensurable units [37].

A significant methodological advancement addressing the limitations of AHP is the Best-Worst Method (BWM) proposed by Rezaei [15]. BWM simplifies the weighting process by having decision-makers identify only the most important (Best) and least important (Worst) criteria. They then perform pairwise comparisons between these two extremes and all other criteria. This structured approach requires only $2n-3$ comparisons, significantly reducing the time required and, more importantly, yielding comparison vectors that consistently produce a lower Consistency Ratio (CR) than AHP [38]. The higher data consistency enhances the reliability of the derived weights. This efficiency and robustness make BWM particularly advantageous for complex decision hierarchies, such as the one required for shared mobility planning with its numerous technical and socio-economic sub-criteria. The synergistic combination of BWM for precise weight derivation and TOPSIS for intuitive alternative ranking is an emerging and powerful hybrid MCDM approach that has shown promise in fields like renewable energy planning and supply chain management, but its application in urban transport infrastructure prioritization remains under-explored [39], [40].

Recent applications demonstrate BWM's effectiveness in transport planning contexts. Yıldızhan et al. [41] successfully combined BWM with TOPSIS to evaluate public transport options for cities of different scales (Eskişehir and Istanbul), demonstrating that the hybrid approach can effectively handle both monetary and non-monetary impacts. Trivedi et al. [14] applied hybrid BWM-TOPSIS to prioritize road safety improvements, further validating the methodology's suitability for transport prioritization problems. Moslem et al. [42] employed advanced MCDM techniques for park-and-ride facility location selection, while Aquilué Junyent et al. [10] directly applied MCDA to shared mobility hub planning in Barcelona, providing a crucial European precedent for the present study.

2.3 Synthesizing the gap: The need for a zonal prioritization framework

A critical synthesis of the two reviewed streams of literature reveals a conspicuous and operationally significant research gap. On one hand, the literature unequivocally establishes the physical infrastructure dependencies of shared mobility systems and frames their deployment as a civil engineering challenge. On the other hand, the MCDM toolkit, especially advanced methods like BWM and TOPSIS, offers proven, rigorous methodologies for solving multi-objective resource allocation problems in urban planning.

However, these domains intersect only superficially in current research. Existing MCDM applications in shared mobility are predominantly focused on micro-level, GIS-intensive optimization —for example, identifying the exact geospatial coordinates for individual docking stations or charging points to maximize coverage or minimize walking distance [43], [44]. While valuable, this granular focus often requires highly detailed spatial data and computational models that may not be accessible or practical for municipal engineers in the early, strategic phases of city-wide planning and budget allocation.

Conversely, broader studies on shared mobility policy often discuss infrastructure in general terms without providing a structured, quantitative methodology to answer the fundamental strategic question faced by city planners: Given multiple urban districts or zones with different characteristics, and limited capital, where should we invest in shared mobility infrastructure first?

Therefore, there is a pressing need for a decision-support framework that operates at the intermediate, zonal planning level. This framework must be: (1) Structured, incorporating the multi-dimensional criteria relevant to civil engineering (technical feasibility, demand, environment, equity); (2) Robust, employing advanced MCDM techniques like BWM-TOPSIS to ensure methodological rigor and reliable outputs; (3) Accessible, not reliant on highly specialized GIS analysis for its core function, making it usable with commonly available urban data and expert judgment; and (4) Actionable, producing a clear priority ranking to guide phased investment and master planning.

This study is designed to fill this precise gap. It develops and demonstrates a novel, hierarchical BWM-TOPSIS framework specifically for the zonal prioritization of shared mobility infrastructure investment. By providing a transparent, reproducible, and multi-criteria tool, this research contributes directly to the civil engineering practice of sustainable urban transport planning, enabling more evidence-based and equitable infrastructure investment decisions.

3 Methodology

3.1 Framework overview and hierarchical structure

This study proposes an integrated Multi-Criteria Decision-Making (MCDM) framework, combining the Best-Worst Method (BWM) for criteria weighting with the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) for alternative ranking. The framework is designed to address the strategic, city-wide question of prioritizing urban zones for investment in physical shared mobility infrastructure (e.g., designated parking/charging hubs). Its development follows a three-phase process, visualized in Fig. 1: (1) Problem Structuring & Hierarchy Definition, (2) Criteria Weighting via BWM, and (3) Alternative Evaluation & Ranking via TOPSIS.

The decision problem is structured into main & sub levels hierarchy. The overarching Goal is to prioritize urban zones for shared mobility hub investment. This goal is evaluated against five Main Criteria, identified as critical dimensions for civil engineering planning:

- C1: Transport connectivity & integration;
- C2: Demand density & latent usage;
- C3: Infrastructure readiness & suitability;
- C4: Environmental & urban impact;
- C5: Social equity & accessibility improvement.

Each main criterion is further decomposed into 17 measurable Sub-Criteria, detailed in Table 1, to ensure a comprehensive and precise evaluation. This hierarchical decomposition allows for a nuanced assessment that captures both high-level strategic objectives and specific, actionable engineering and planning concerns.

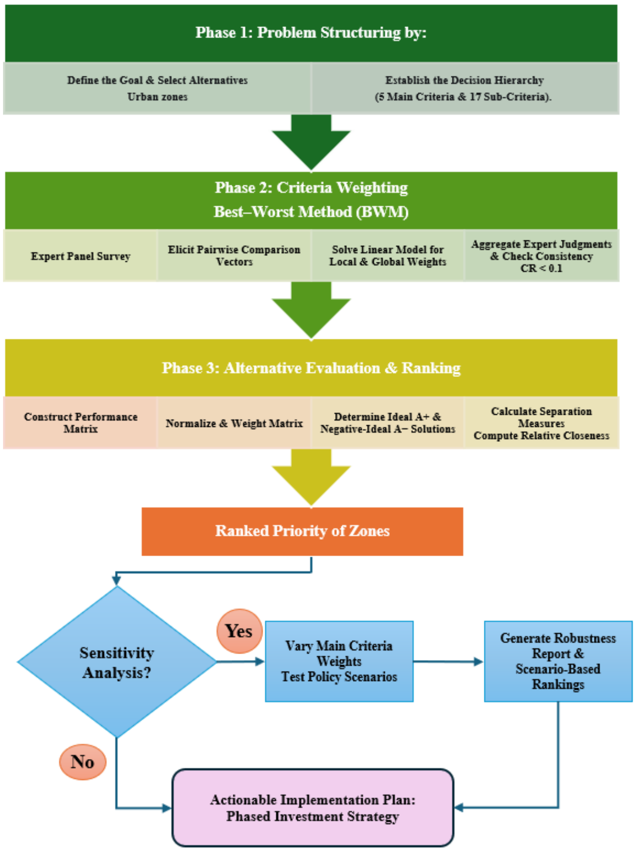

Fig. 1 Proposed BWM-TOPSIS framework for shared mobility infrastructure zonal prioritization

3.2 Zone delineation and case study scope

The four urban zones evaluated in this study were selected to represent a typologically diverse cross-section of Budapest's built environment, ensuring that the framework is tested across contrasting urban conditions rather than similar contexts. Zone selection followed two principles: (1) administrative coherence, whereby each zone corresponds to one or more contiguous Budapest districts sharing comparable morphological and functional characteristics; and (2) functional differentiation, whereby the selected zones collectively span the full spectrum of urban typologies relevant to shared mobility planning – from a dense historic core to a peripheral residential suburb.

Specifically, Zone A (Belváros–Lipótváros) represents the Historic Central Business District, characterized by high density, heritage constraints, and strong transit connectivity. Zone B (Újlipótváros–Angyalföld) represents a Mixed-Use Residential Corridor with high population density and growing multimodal demand. Zone C (Kelenföld–Albertfalva) represents a Major Transport Hub and University Area, anchored by a major rail interchange and a university campus. Zone D (Péterhegy–Kőbánya) represents an Outer Residential Suburb, characterized by lower density, limited transit coverage, and greater car dependence. Together, these four typologies capture the planning trade-offs most commonly encountered in Central European cities undergoing

Table 1 Decision hierarchy: Main criteria and sub-criteria

Main criterion	Sub-criteria	Description
C1: Transport connectivity	C1.1 Multimodal node proximity	Density of and proximity to major public transport nodes (metro, rail).
	C1.2 Service frequency & coverage	Quality of existing service (headways, spatial coverage).
	C1.3 Pedestrian access quality	Safety and convenience of pedestrian routes to/from transport nodes.
	C1.4 First-/Last-mile effectiveness	Potential to solve critical first- or last-mile gaps in the transport network.
C2: Demand density	C2.1 Residential population density	Concentration of the resident population within the zone.
	C2.2 Employment & activity density	Concentration of jobs, universities, and other trip attractors.
	C2.3 Current mobility pain points	Severity of existing transport deficiencies (congestion, parking scarcity).
C3: Infrastructure readiness	C3.1 Public right-of-way availability	Physical space in the public realm suitable for hub installation.
	C3.2 Utility access & grid capacity	Ease of connecting to electrical grid and other utilities.
	C3.3 Surface & geotechnical suitability	Ground conditions and pavement quality for construction.
	C3.4 Digital infrastructure support	Quality of cellular and data network coverage for IoT operations.
C4: Environmental impact	C4.1 Local air quality improvement potential	Potential to reduce local pollutant emissions from private vehicles.
	C4.2 Energy efficiency	Expected energy consumption per trip, considering system operations.
	C4.3 Modal shift contribution	Potential to cause a net shift from private motorized to shared modes.
C5: Social equity	C5.1 Affordability for low-income users	Potential to offer accessible pricing and serve lower-income groups.
	C5.2 Geographic inclusiveness	Ability to extend quality mobility options to underserved areas.
	C5.3 Universal accessibility	Potential to improve mobility for disabled, elderly, or mobility-impaired users.

shared mobility expansion, and enable the framework to produce findings with transferable relevance beyond the Budapest context.

3.3 Phase 1: Determining criteria weights using BWM

The Best-Worst Method (BWM) is employed to determine the relative importance (weights) of the criteria, as it requires fewer pairwise comparisons and yields more consistent results than methods like AHP [15].

Step 1: Expert Panel Selection. A panel of $K = 29$ experts ($k = 1, 2, \ldots, K$) is formed, comprising civil engineers specializing in transport, urban planners, and municipal infrastructure managers with direct knowledge of the case study city. This ensures weights reflect professional, grounded judgment.

Step 2: Eliciting Best-to-Others and Others-to-Worst Vectors. For the main criteria weighting, each expert k is asked to identify:

- The most important (Best, B) main criterion.
- The least important (Worst, W) main criterion.

The expert then provides two vectors of pairwise comparisons on a scale of 1 to 9 (where 1 indicates equal importance and 9 indicates extreme importance of the Best over another criterion, or of another criterion over the Worst):

- Best-to-Others (BO) vector: $\boldsymbol{a}_b^k = \left(a_{b1}^k, a_{b2}^k, \ldots, a_{b5}^k\right)$, where a_{bj}^k is the preference of the Best criterion over criterion j for expert k.
- Others-to-Worst (OW) vector: $\boldsymbol{a}_w^k = \left(a_{1w}^k, a_{2w}^k, \ldots, a_{5w}^k\right)^T$, where a_{jw}^k is the preference of criterion j over the Worst criterion.

This process is repeated at the sub-criteria level. Each expert performs a separate BWM evaluation within each main criterion group to determine the local importance of the sub-criteria relative to each other.

Step 3: Calculating Optimal Weights and Consistency. For each expert k, the optimal weights for the five main criteria $\boldsymbol{w}^k = \left(w_1^k, w_2^k, w_3^k, w_4^k, w_5^k\right)$ are obtained by solving the following linear programming model (presented for the main criteria; the model for sub-criteria is analogous):

$$\begin{aligned}
&\text{Minimize } \xi^k \\
&\text{Subject to:} \\
&\left|w_B^k - a_{Bj}^k w_j^k\right| \le \xi^k, \text{ for all } j \\
&\left|w_j^k - a_{jw}^k w_w^k\right| \le \xi^k, \text{ for all } j \\
&\sum_{j=1}^{5} w_j^k = 1 \\
&w_j^k \ge 0, \text{ for all } j
\end{aligned} \quad . \tag{1}$$

Where ξ^k is the consistency index for expert k. The optimal solution provides the weight vector $\boldsymbol{w}^{*k}$ and the minimal ξ^{*k}. The Consistency Ratio (CR) is calculated as $CR^k = \xi^{*k}/$ Consistency Index (CI), where CI is a known value corresponding to a_{BW}^k [38]. A $CR \le 0.10$ is considered acceptable, indicating reliable judgments.

Step 4: Aggregating Expert Judgments. After verifying consistency, the individual expert weight vectors are aggregated. The geometric mean is used to preserve the ratio scale property of the weights. For the main criteria, the aggregated weight w_j^{main} for criterion j is:

$$w_j^{main} = \frac{\left(\Pi_{k=1}^K w_j^{*k}\right)^{1/K}}{\sum_{i=1}^{5}\left(\Pi_{k=1}^K w_i^{*k}\right)^{1/K}} . \tag{2}$$

The same process yields the local weights for sub-criteria within each main criterion group, denoted as $w_{s/c}^{\text{local}}$ for sub-criterion s given main criterion c.

Step 5: Calculating Global Weights for Sub-Criteria. To integrate the full hierarchy for the TOPSIS analysis, the global weight w_s^{global} for each of the 17 sub-criteria is calculated by multiplying its local weight by the weight of its parent main criterion:

$$w_s^{\text{global}} = w_c^{\text{main}} \times w_{s/c}^{\text{local}} . \tag{3}$$

These 17 global weights sum to 1.0 and are used directly in the subsequent TOPSIS procedure, ensuring the entire hierarchical importance structure is respected in the final ranking.

3.4 Phase 2: Evaluating and ranking alternatives using TOPSIS

With the criteria weights established, the TOPSIS method is applied to rank the m alternative zones ($i = 1, 2, ..., m$).

Step 1: Construct the Performance Decision Matrix. A performance matrix $\boldsymbol{X} = \left[x_{i,j}\right]_{m \times n}$ is constructed, where x_{ij} represents the performance score of alternative i on sub-criterion j ($n = 17$). These scores are obtained via a structured expert survey. For each zone, experts rated its performance on each of the 17 sub-criteria using a 1–7 Likert scale (1 = Very Poor, 7 = Very Good). The scores from all experts were averaged to populate the matrix.

Step 2: Normalize the Decision Matrix. To enable comparison across criteria measured on different scales, the matrix is normalized using the vector normalization method. The normalized value r_{ij} is calculated as:

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}} . \tag{4}$$

Vector normalization was selected over alternatives such as linear (min-max) normalization because it preserves the relative distances between scores in a scale-invariant manner, is not sensitive to outliers or extreme values, and is particularly well-suited to Likert-scale data, where the ratio relationships between scores are meaningful [34].

This results in the normalized matrix $\boldsymbol{R} = \left[r_{ij} \right]_{m \times n}$.

Step 3: Construct the Weighted Normalized Decision Matrix. The normalized matrix is multiplied by the diagonal matrix of the global weights derived from BWM:

$$v_{ij} = w_j^{global} \times r_{ij} . \tag{5}$$

This yields the weighted normalized matrix $\boldsymbol{V} = \left[v_{ij} \right]_{m \times n}$, where w_j^{global} is the global weight of the *j*-th sub-criterion.

Step 4: Determine the Ideal and Negative-Ideal Solutions. Since all sub-criteria are defined as benefits (higher score is better), the ideal solution A^+ and the negative-ideal solution A^- are defined as:

$$\begin{aligned} A^+ &= \left\{ v_1^+, v_2^+, \ldots, v_n^+ \right\} = \left\{ \left(\max_i v_{ij} \,|\, j = 1, 2, \ldots, n \right) \right\} \\ A^- &= \left\{ v_1^-, v_2^-, \ldots, v_n^- \right\} = \left\{ \left(\min_i v_{ij} \,|\, j = 1, 2, \ldots, n \right) \right\} \end{aligned} . \tag{6}$$

Step 5: Calculate the Separation Measures. The Euclidean distance of each alternative from the ideal and negative-ideal solutions is calculated:

$$\begin{aligned} S_i^+ &= \sqrt{\sum\nolimits_{j=1}^{n} \left(v_{ij} - v_j^+ \right)^2} \\ S_i^- &= \sqrt{\sum\nolimits_{j=1}^{n} \left(v_{ij} - v_j^- \right)^2} \end{aligned} . \tag{7}$$

Step 6: Calculate the Relative Closeness to the Ideal Solution. The relative closeness C_i of each alternative to the ideal solution is computed:

$$C_i = \frac{S_i^-}{S_i^+ + S_i^-}, 0 \le C_i \le 1 . \tag{8}$$

Step 7: Rank the Alternatives. The alternatives are ranked in descending order of C_i. The alternative with the highest C_i value is the most preferred, as it is simultaneously closest to the ideal solution and farthest from the negative-ideal solution.

3.5 Sensitivity analysis

To test the robustness of the ranking and the influence of the criterion weights, a sensitivity analysis is conducted. The weights of the main criteria are systematically varied (e.g., ±20% of their baseline value) to create different policy scenarios (e.g., "Demand-Focused," "Equity-Focused," "Sustainability-Focused"). The TOPSIS ranking is recalculated for each scenario. The stability of the top-ranked alternative(s) across these scenarios indicates the robustness of the recommendation, while significant changes highlight which criteria act as key drivers of the ranking and reveal inherent trade-offs in the decision problem.

4 Results and analysis

4.1 Case study: Budapest's urban context and zone selection

To demonstrate the practical application of the proposed BWM-TOPSIS framework, Budapest, Hungary, was selected as the case study city. Budapest presents a classic Central European urban structure, characterized by a dense historic core, socialist-era housing estates, modern mixed-use developments, and residential suburbs, providing an ideal laboratory for testing zonal prioritization logic. As described in Section 3.2, four distinct zones were delineated according to principles of administrative coherence and functional differentiation, each representing a dominant urban typology relevant to shared mobility planning. The zones and their boundaries are illustrated in Fig. 2, and their key characteristics are summarized in Table 2.

4.2 BWM weighting results

A panel of 29 experts (K=29) from Hungarian academia, the Budapest Transport Centre (BKK), and municipal planning departments completed the BWM surveys. All individual comparisons yielded Consistency Ratios (CR) below the 0.10 threshold, confirming reliable judgments [45]. The aggregated local and global weights are presented in Table 3 and visualized in Fig. 3.

Key Findings from BWM: The expert panel identified Transport Connectivity (C1) as the most critical main criterion (31%), followed closely by Demand Density (C2) at (24%). At the sub-criteria level, C1.1 Multimodal Node Proximity (12.8%) and C2.3 Current Mobility Pain Points (9.3%) emerged as the two most influential factors, underscoring the expert view that infrastructure must be integrated at key transport nodes and address existing deficiencies. C3.1 Public Right-of-Way Availability (5.9%) was the highest-ranked infrastructure sub-criterion, highlighting space as a primary practical constraint. The results reflect a balanced yet pragmatic priority set, weighing immediate operational concerns (connectivity, demand) significantly but not excluding environmental (C4.3: 8.8%) and social (C5.1: 5.7%) objectives.

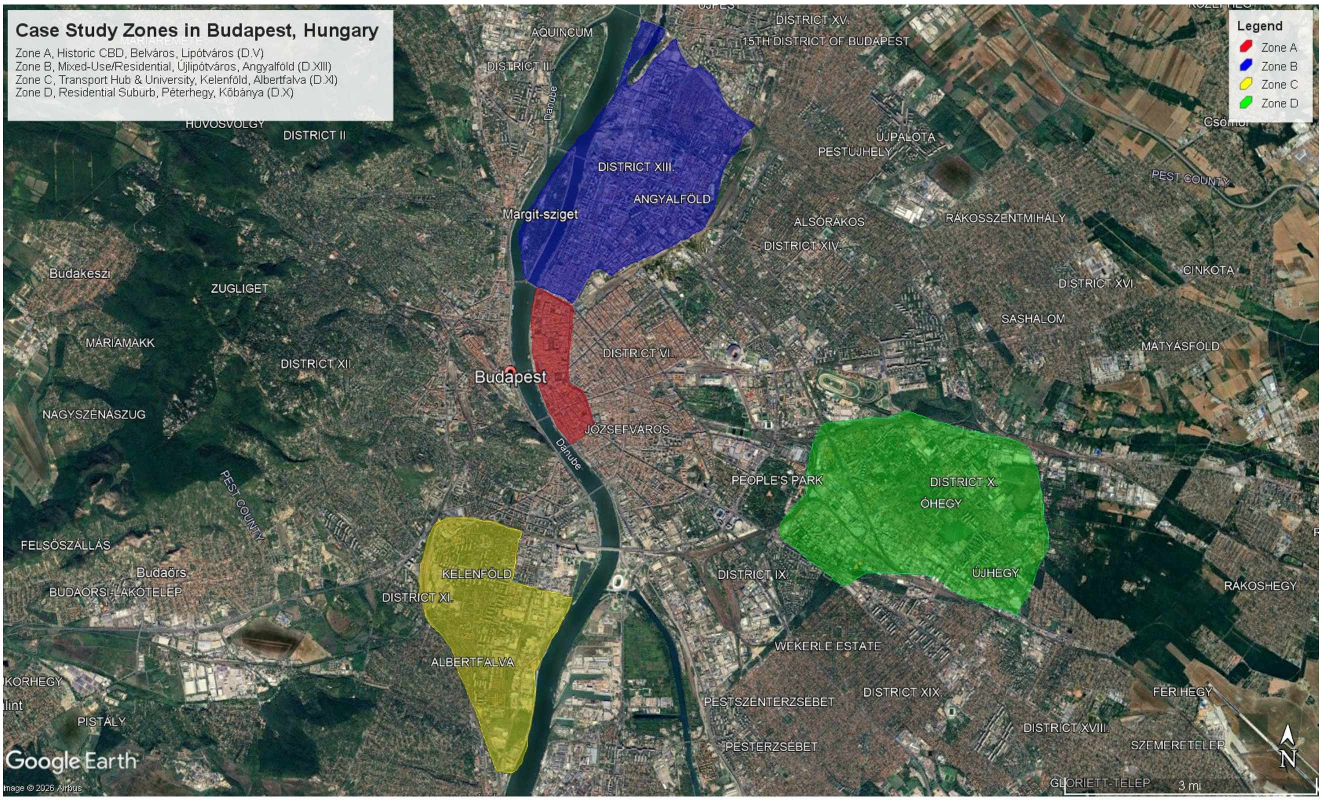

Fig. 2 Case study zones in Budapest, Hungary

Table 2 Description of the four evaluated urban zones in Budapest

Zone	Name & district	Key characteristics	Rationale for selection
A	Belváros - Lipótváros (District V)	Historic central business district (CBD). High concentration of offices, government, tourism, and retail. Very low residential population, extremely high daytime density. Heritage-protected urban fabric with narrow streets.	Represents the challenge of deploying new infrastructure in a high-demand, space-constrained historic core. Tests the model under maximum pressure.
B	Újlipótváros - Angyalföld (District XIII, North)	Mixed-use, high-density residential & modern office corridor. Young, affluent demographic. High-rise apartments and modern offices. Good public transport and developing cycling infrastructure.	Represents a prime candidate for adoption—a dynamic, growing area with strong demand and more implementation space than the CBD.
C	Kelenföld - Albertfalva (District XI, West)	Major transport hub & university area. Centered on Kelenföld station (rail, Metro M4, bus/tram interchange). Adjacent residential areas of variable density. Serves a large student population and regional commuters.	Tests the model's ability to prioritize integration with heavy rail and address "last-mile" connectivity from a major multi-modal node.
D	Péterhegy - Kőbánya (District X, East)	Traditional residential suburb with regeneration potential. Lower-density, mixed housing types. Lower average income, older demographic. Reliant on buses and the terminal end of Metro M3. More available public space.	Represents the challenge of extending service to lower-density, potentially underserved areas where demand is latent but equity and environmental benefits could be high.

4.3 TOPSIS evaluation and final ranking

The performance scores for the four zones across the 17 sub-criteria, aggregated from the expert survey (1-7 scale), form the decision matrix as shown in Table 4. These scores were normalized, weighted using the global weights from Table 3, and processed through the TOPSIS algorithm.

The TOPSIS calculations yielded the separation measures (S_i^+, S_i^-) and relative closeness coefficients (C_i) for each zone, leading to the final ranking (Table 5, Fig. 4).

The TOPSIS analysis yields a clear priority ranking (Table 5): Zone B ranks first (C_i = 0.7319), followed by Zone A (C_i = 0.5792), Zone C (C_i = 0.5644), and Zone D (C_i = 0.3962).

Zone B is the optimal candidate due to its balance: it records the smallest distance from the ideal solution (S^+ = 0.0177) while maintaining a substantial distance from the negative-ideal (S^- = 0.0484). It performs strongly on high-weight demand criteria (C2.2, C2.3) and avoids

Table 3 Aggregated BWM weights: Local (within group) and global (overall)

Level	Criterion code	Criterion name	Local weight	Global weight	Rank (global)
Main	C1	Transport connectivity & integration	0.3099	0.3099	–
	C2	Demand density & latent usage	0.2410	0.2410	–
	C3	Infrastructure readiness & suitability	0.1708	0.1708	–
	C4	Environmental & urban impact	0.1594	0.1594	–
	C5	Social equity & accessibility improvement	0.1189	0.1189	–
Sub (C1)	C1.1	Multimodal node proximity	0.4126	0.1279	1
	C1.2	Service frequency & coverage	0.2533	0.0785	5
	C1.3	Pedestrian access quality	0.1640	0.0508	10
	C1.4	First-/Last-mile effectiveness	0.1701	0.0527	9
Sub (C2)	C2.1	Residential population density	0.2396	0.0577	7
	C2.2	Employment & activity density	0.3755	0.0905	3
	C2.3	Current mobility pain points	0.3848	0.0928	2
Sub (C3)	C3.1	Public right-of-way availability	0.3449	0.0589	6
	C3.2	Utility access & grid capacity	0.1984	0.0339	14
	C3.3	Surface & geotechnical suitability	0.2908	0.0497	11
	C3.4	Digital infrastructure support	0.1659	0.0283	16
Sub (C4)	C4.1	Local air quality improvement potential	0.2428	0.0387	13
	C4.2	Energy efficiency	0.2062	0.0329	15
	C4.3	Modal shift contribution	0.5510	0.0878	4
Sub (C5)	C5.1	Affordability for low-income users	0.4756	0.0566	8
	C5.2	Geographic inclusiveness	0.1882	0.0224	17
	C5.3	Universal accessibility	0.3363	0.0400	12

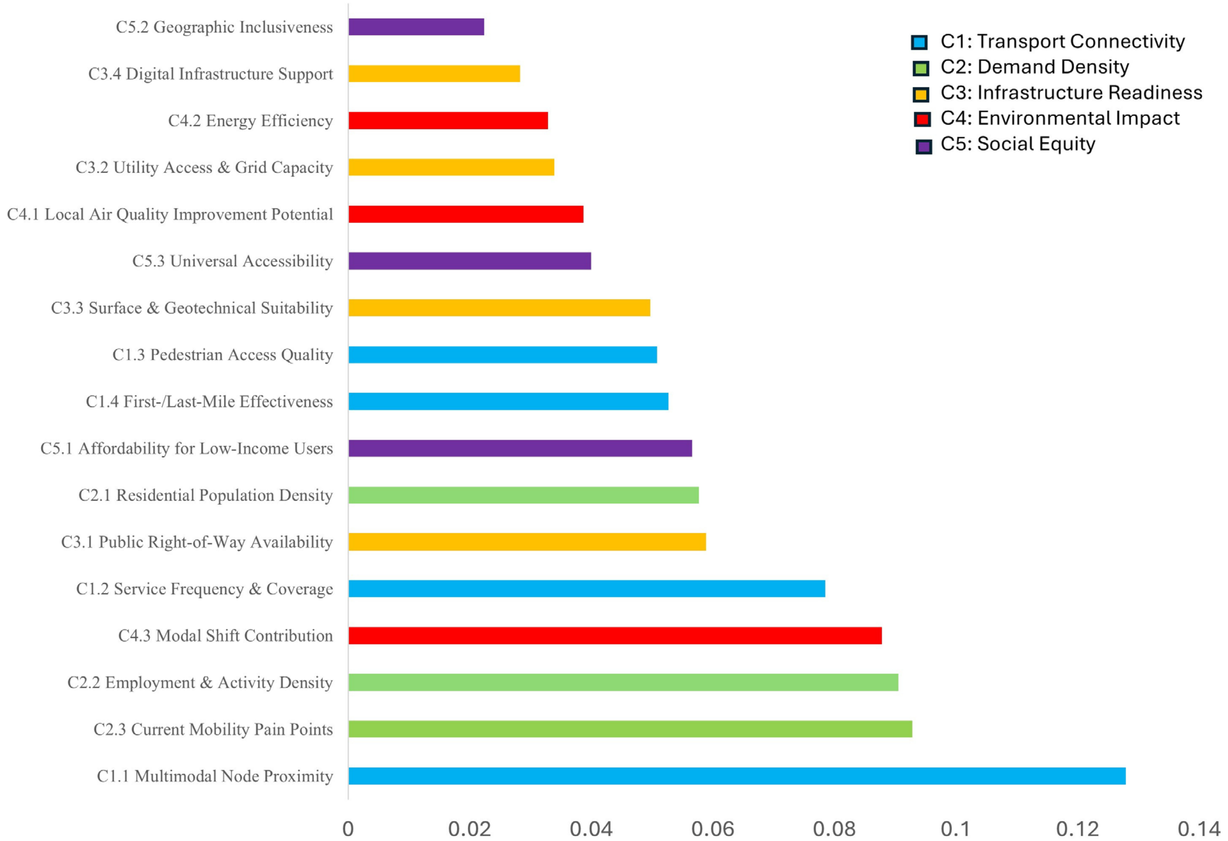

Fig. 3 Global weight distribution of the 17 Sub-Criteria

Table 4 Performance matrix: Zone ratings on 17 sub-criteria (Scale 1-7)

Zone	A	B	C	D
C1.1	6.8	5.9	6.7	3.8
C1.2	6.9	6.3	5.8	4.1
C1.3	4.6	5.8	5.2	5.1
C1.4	5.3	5.9	6.3	3.9
C2.1	3.5	6.2	4.8	5.1
C2.2	6.7	6.4	4.3	3.8
C2.3	6.9	5.8	4.9	4.2
C3.1	2.8	5.7	4.9	6.3
C3.2	6.2	5.9	5.6	5.1
C3.3	3.8	5.6	5.2	6.1
C3.4	6.5	6.2	5.8	4.8
C4.1	4.2	5.6	4.1	6.3
C4.2	4.8	5.9	4.3	6.1
C4.3	5.1	6.1	5.7	6.5
C5.1	3.7	4.8	5.6	6.2
C5.2	3.2	5.2	5.9	6.5
C5.3	3.5	5.4	5.3	6.1

Table 5 TOPSIS calculation results and final ranking

Zone	Distance from ideal (S_i^+)	Distance from negative-ideal (S_i^-)	Relative closeness (C_i)	Rank
A (Historic CBD)	0.0368	0.0506	0.5792	2
B (Mixed-use)	0.0177	0.0484	0.7319	1
C (Transport hub)	0.0325	0.0421	0.5644	3
D (Residential suburb)	0.0520	0.0341	0.3962	4

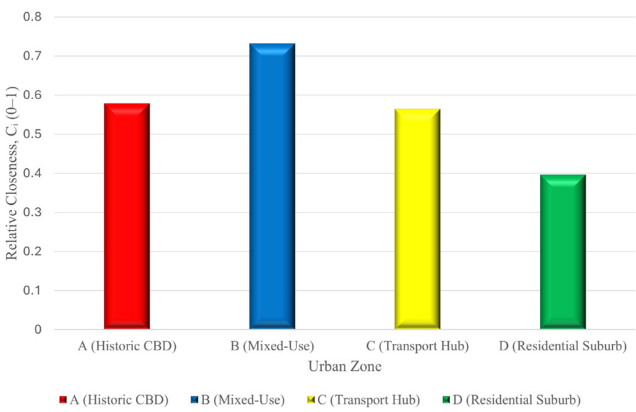

Fig. 4 Final ranking of zones based on TOPSIS relative closeness C_i

critical infrastructure weaknesses, representing the strategic convergence of demand, feasibility, and readiness.

Zone A ranks second despite excelling on the two highest-weighted sub-criteria–C1.1 (Multimodal Node Proximity) and C2.3 (Mobility Pain Points)—and achieving the largest distance from the negative-ideal (S^- = 0.0506). However, its distance from the ideal (S^+ = 0.0368) is double that of Zone B, driven by the lowest score for C3.1 (Public Right-of-Way Availability). This reveals a pivotal trade-off: supreme demand cannot compensate for the absence of deployable public space.

Zone C places third with a specialized profile. It records the second-smallest distance from the ideal (S^+ = 0.0325), driven by exceptional connectivity scores (C1.1, C1.4) reflecting its role as a major rail hub. However, moderate performance on demand and equity criteria limits its broader candidacy, positioning it as a tactical system-integration asset rather than a primary investment zone.

Zone D ranks fourth, presenting the model's most instructive paradox. It achieves the largest distance from the ideal (S^+ = 0.0520)due to poor scores on high-weight connectivity criteria, yet simultaneously records the highest scores for environmental impact (C4.1, C4.3), social equity (C5.1, C5.2), and critically, C3.1 (Public Right-of-Way Availability) . Zone D is the inverse of Zone A: abundant space and strategic potential, but weak current demand. Its low baseline ranking reflects expert prioritization of immediate operational success; however, sensitivity analysis confirms that modest weight shifts toward sustainability or equity elevate it to top-tier status.

The central finding is a fundamental trade-off: zones with the highest immediate demand face the most severe implementation constraints, while zones with the greatest long-term strategic potential exhibit the weakest current performance. Zone B succeeds because it is the only zone that escapes this dichotomy, possessing both robust demand and adequate physical space. This underscores that rational infrastructure investment cannot simply follow demand—it must explicitly balance operational, spatial, environmental, and equity objectives.

4.4 Sensitivity analysis

To assess the robustness of the ranking and examine how shifts in policy priorities would affect investment decisions, a systematic sensitivity analysis was conducted by varying the weights of the five main criteria. Four alternative scenarios were developed against the Baseline (Expert Consensus) weights derived from the BWM survey. Each scenario represents a distinct strategic orientation that a municipal decision-maker might adopt. The TOPSIS algorithm was fully recalculated for each scenario using the same normalized performance matrix, with new global weights computed from the adjusted main criteria weights and the fixed local sub-criteria weights. The results are presented in Table 6; the multi-criteria performance profile of each zone across all five main criteria dimensions is further visualized in Fig. 5.

Zone B demonstrates exceptional rank stability, holding first position in Baseline and in three of the four alternative scenarios (S1, S2, S3). Its relative closeness coefficient remains consistently high, ranging from 0.712 to 0.748 across these scenarios. This stability is driven by its balanced performance profile: Zone B scores above average on all five main criteria and avoids the critical weaknesses that plague other zones. Even in S4 (Equity & Environment-Focused), where it cedes first place to Zone D, it maintains a strong second-place position with $C_i = 0.587$. This confirms Zone B as a low-risk, no-regrets investment that performs well under diverse strategic orientations, making it the recommended lead investment under conditions of uncertainty.

Zone D exhibits the highest sensitivity to weighting shifts. It rises from fourth place in Baseline (C_i = 0.396) to first place in S4 (Equity & Environment-Focused) with C_i = 0.631. This dramatic improvement is driven by its top-ranked performance on the criteria that become most heavily weighted in this scenario: C4.3 Modal Shift Contribution, C5.1 Affordability for Low-Income Users, and critically, C3.1 Public Right-of-Way Availability. When sustainability and social equity are prioritized, Zone D transforms from the lowest-ranked to the highest-ranked zone.

This finding demonstrates that Zone D is not a universally weak candidate, but rather a strategically valuable asset whose priority depends entirely on municipal policy goals. Cities pursuing EU cohesion funding, climate neutrality commitments, or social inclusion mandates would rationally elevate Zone D to first position. The framework thus provides decision-makers with a clear, quantitative lever to align infrastructure investment with political priorities.

Zone A shows moderate sensitivity. It holds second place in Baseline and S1, drops to third in S2, and falls to fourth in S4. Its performance deteriorates under connectivity-focused weighting because it is already at the maximum—further emphasizing this dimension does not improve its relative position. Under equity and environment-focused weighting, its poor social equity scores become heavily penalized, causing its collapse to last place. Zone A is therefore an excellent candidate only when demand and connectivity are the exclusive priorities; it performs poorly when broader sustainability objectives are emphasized.

Zone C maintains third or fourth position across all scenarios, rising to second only in S2 (Connectivity-Focused). This confirms its role as a specialized, context-dependent asset rather than a broadly competitive candidate. Its optimal deployment is as a tactical investment to integrate shared mobility with regional rail, best executed after the system is established elsewhere.

Four principal conclusions emerge from the sensitivity analysis:

1. No single zone dominates all policy scenarios. The optimal investment priority is not absolute but contingent on explicit value judgments about what the shared mobility system should achieve. This validates the necessity of multi-criteria decision frameworks in infrastructure planning.
2. Zone B is the most robust choice. Ranking first or second in all five scenarios, it represents the recommended lead investment under uncertainty and serves as an ideal pilot zone for system launch.
3. Zone D is the most policy-responsive zone. Its ranking is a direct function of how heavily sustainability and equity are weighted, providing municipal decision-makers with a clear, quantifiable mechanism to translate political mandates into investment priorities.
4. The framework successfully captures and quantifies trade-offs. The sensitivity analysis demonstrates that the BWM-TOPSIS model does not obscure conflict between competing objectives but rather

Table 6 Sensitivity analysis: Ranking stability under different weighting scenarios

Scenario	Baseline	S1	S2	S3	S4
Primary focus	Expert consensus	Demand-focused	Connectivity-focused	Infrastructure-focused	Equity & environment-focused
Weight adjustment	C1:0.3099, C2:0.2410, C3:0.1708, C4:0.1594, C5:0.1189	C2: +20% (0.2892), others reduced proportionally	C1: +20% (0.3719), others reduced proportionally	C3: +20% (0.2050), others reduced proportionally	C4: +50% (0.2391), C5: +50% (0.1784), C1/C2 reduced
1st (C_i)	B (0.732)	B (0.748)	B (0.743)	B (0.712)	D (0.631)
2nd (C_i)	A (0.579)	A (0.629)	C (0.602)	A (0.579)	B (0.587)
3rd (C_i)	C (0.564)	C (0.546)	A (0.591)	C (0.544)	C (0.512)
4th (C_i)	D (0.396)	D (0.381)	D (0.387)	D (0.423)	A (0.408)

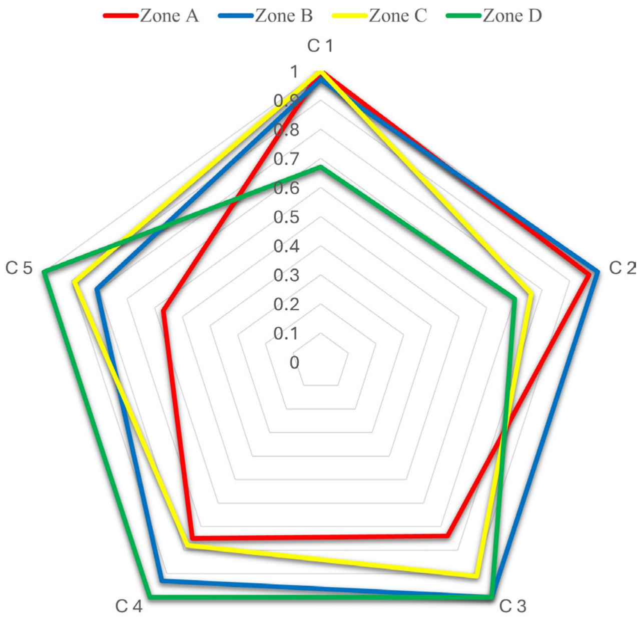

Fig. 5 Radar chart of zone performance across main criteria

renders it transparent and measurable. It enables deliberative, defensible decision-making by showing decision-makers not what to value, but the consequences of their values.

These findings validate the framework's utility as a decision-support tool rather than a decision-prescription tool. It empowers civil engineers and urban planners to move from intuition-based or politically driven allocation toward evidence-based, multi-objective infrastructure investment strategy.

5 Discussion

5.1 Strategic trade-offs and zone performance

The TOPSIS ranking reveals a fundamental tension in shared mobility planning. Zone B ranks first not because it dominates any single criterion, but because it is the only zone that reconciles the core conflict between immediate demand and implementation feasibility. While Zone A and Zone C offer superior connectivity, and Zone D offers superior space and equity, Zone B alone possesses adequate performance across all dimensions simultaneously. Its victory validates a balanced, multi-criteria approach over single-objective optimization.

Zone A's second-place finish is the model's most instructive counter-intuitive finding. Despite achieving the highest possible scores on the two most heavily weighted criteria globally—multimodal proximity and mobility pain points—it is decisively penalized by its severe spatial constraints. This quantifies a critical engineering reality: demand is necessary but not sufficient. In heritage-protected urban cores, physical feasibility acts as a binding constraint that no amount of ridership potential can overcome. Planners who default to "build where demand is highest" would select Zone A and encounter extraordinary implementation costs, prolonged timelines, and compromised design solutions.

Zone D's fourth-place finish under baseline weights is not a verdict on its merit but a reflection of expert weighting priorities. The panel valued immediate operational success over long-term strategic outcomes. However, Zone D possesses three distinct advantages: it has the most available public space, the highest environmental improvement potential, and the strongest social equity profile. When policy weights shift toward sustainability or inclusion–as demonstrated in Scenario S4–Zone D immediately becomes the optimal investment. It is not a weak candidate but a strategic reserve asset, awaiting the political mandate to activate its potential.

Zone C's third-place ranking confirms its role as a specialized asset rather than a general-purpose candidate. Its exceptional connectivity is tied to a single infrastructure asset–Kelenföld station–rather than distributed network advantages. This makes it ideal for targeted system integration but less suitable as a system anchor.

5.2 From ranking to strategy: A phased implementation framework

The ranking translates directly into an actionable investment sequence that manages risk while advancing multiple objectives:

Phase 1 – Pilot and Demonstration (Zone B). Zone B offers the highest probability of operational success. Its balanced profile ensures visible early wins, user adoption, and operational learning. This phase establishes system credibility before expansion into more challenging or uncertain territories.

Phase 2 – Equity and Sustainability Expansion (Zone D). Zone D delivers the greatest social and environmental return per unit investment. Its abundant public space minimizes construction complexity and cost. This phase operationalizes commitments to climate justice and transport equity, extending benefits beyond affluent central districts.

Phase 3 – System Integration (Zone C). With the system established, Zone C maximizes network effects by capturing regional rail commuters. This phase completes the first-/last-mile connection and integrates shared mobility with Budapest's broader transport network.

Phase 4 – CBD Innovation (Zone A). The most challenging and expensive zone is deliberately deferred. By Phase 4, the system has sufficient scale and financial maturity to invest in bespoke, heritage-sensitive solutions–micro-hubs, automated storage, or public-private partnerships.

This sequencing ensures that no single objective is pursued to the exclusion of others. It balances operational viability, environmental impact, social equity, and system integration across a realistic, multi-year investment horizon.

Furthermore, the BWM weighting process itself is a powerful policy tool. The baseline weights represent a "professional consensus" scenario. Municipal leaders can adjust these weights to steer outcomes:

- An "Equity-First" Policy: Increasing the weight of C5 (Social Equity) and C5.2 (Geographic Inclusiveness) would elevate Zone D to the top priority, as shown in S4 (Equity & Environment-Focused).
- A "Congestion Relief" Policy: Increasing the weight of C2.3 (Current Mobility Pain Points) and C4.3 (Modal Shift Contribution) would further solidify the case for Zones A and B.
- A "Fast Deployment" Policy: Increasing the weight of C3 (Infrastructure Readiness) would prioritize Zone D and potentially Zone B, favoring areas where projects can be completed quickly and under budget.

This adjustability allows the same transparent framework to serve different political mandates or strategic planning cycles.

5.3 Validation, framework limitations and contribution

The plausibility of the results serves as primary validation. The ranking aligns with professional intuition–Zone B is widely recognized as a growth corridor ripe for new mobility–while providing quantitative rigor to challenge assumptions such as the CBD's prima facie attractiveness. Further validation could involve: (1) back-testing with BUBI bike-share usage data; (2) stakeholder workshops to assess face validity; and (3) comparison with traditional cost-benefit analysis.

Several limitations warrant acknowledgment. The framework relies on expert judgment, introducing subjectivity, though BWM's consistency checks ($CR < 0.10$) and aggregation across 29 experts mitigate individual bias. The analysis is static, excluding network effects and induced demand. The zonal level is a strategic strength for master planning but requires subsequent GIS-based micro-siting for site-specific implementation. Finally, the criteria hierarchy reflects Budapest's urban context and would require recalibration – including potentially different criteria or weight ranges – before direct application to cities with substantially different morphological, institutional, or cultural characteristics.

A key avenue for addressing the static nature of the analysis lies in the integration of dynamic and real-time data. Future iterations of the framework could incorporate time-dependent mobility indicators – such as origin-destination flows derived from mobile network data, real-time public transport occupancy, or seasonal variation in shared vehicle usage – to produce scenario-aware rankings that reflect how zone priorities may shift across peak and off-peak conditions. This would significantly enhance the framework's practical responsiveness and its alignment with emerging smart city data infrastructures.

This study provides four distinct advances:

1. Transparency and Auditability. Every step–criterion definition, weighting, normalization, separation measures–is explicit and documented. Decision-makers can trace precisely why Zone B outranks Zone A, enabling public accountability.
2. Consensus-Building Utility. The BWM process forces structured deliberation among experts from transport, environment, and social services. The resulting weights represent a synthesized, justified consensus, aligning departmental perspectives that typically operate in silos.
3. Handling Complexity and Conflict. The framework does not omit difficult-to-quantify criteria such as equity or environmental impact. It quantifies trade-offs between pavement quality and geographic inclusiveness, making conflicts visible and debatable rather than hidden.
4. Flexibility and Transferability. The hierarchical structure can be adapted by adding, removing, or re-weighting criteria for local context. The methodology requires no proprietary software or intensive GIS capacity, enhancing accessibility for municipal planning departments.

In summary, this study demonstrates that advanced MCDM techniques are not merely academic exercises but essential tools for rational, defensible, and equitable infrastructure investment. By operationalizing sustainability and equity as quantifiable criteria, the framework empowers civil engineers to balance technical feasibility with long-term urban goals.

6 Conclusion

This study addressed a critical gap in the planning of sustainable urban transport systems: how should municipal engineers and planners objectively prioritize urban zones for investment in physical shared mobility infrastructure amidst multiple conflicting criteria? To answer this, an integrated BWM-TOPSIS decision framework was developed, incorporating 17 sub-criteria across five dimensions fundamental to civil engineering: Transport Connectivity, Demand Density, Infrastructure Readiness, Environmental Impact, and Social Equity. Applied to a case study of Budapest, the framework evaluated four distinct urban typologies—the Historic CBD, a Mixed-Use Corridor, a Transport Hub, and a Residential Suburb. Zone selection followed principles of administrative coherence and functional differentiation, as detailed in Section 3.2, ensuring that the four typologies collectively represent the full spectrum of urban conditions relevant to shared mobility planning.

The key finding is a clear, quantitatively derived priority ranking: Zone B (Újlipótváros - Angyalföld) emerged as the optimal first-priority zone under baseline expert weights, followed by Zone A, Zone C, and Zone D. This result was not determined by any single factor but by Zone B's superior balance across all high-weighted criteria, particularly its strong performance in both demand potential and the critical enabling factor of public right-of-way availability. The fourth-place ranking of the high-demand CBD powerfully illustrates the model's core insight: supreme latent demand can be effectively nullified by insurmountable physical implementation constraints—a trade-off that traditional planning, focused narrowly on ridership projections, might easily overlook.

Equally significant is the policy-responsiveness of Zone D. While ranked fourth under baseline weights, it ascends to first place when sustainability and equity are prioritized. This confirms that the optimal investment sequence is not absolute but contingent on explicit value judgments. Zone D possesses abundant public space, the highest environmental improvement potential, and the strongest social equity profile–assets that remain latent under conventional demand-focused planning but become decisive under a sustainability mandate. The sensitivity analysis demonstrates that the framework does not prescribe what cities should value; rather, it reveals the spatial consequences of those values with quantitative rigor.

The primary contribution of this work is to civil engineering practice in systematic infrastructure investment planning. The proposed framework translates a complex, multi-stakeholder planning dilemma into a transparent, reproducible, and auditable process. It moves decision-making from intuition and political expediency toward evidence-based strategy. By explicitly weighting and evaluating trade-offs between technical feasibility, economic potential, environmental benefit, and social equity, the tool empowers civil engineers to act as stewards of public resources and champions of sustainable, equitable urban development. The adjustability of criteria weights allows the same framework to serve different municipal policy directives, from "fast deployment" to "equity-first" strategies. The use of vector normalization in the TOPSIS stage further ensures that performance scores across heterogeneous criteria are compared on a consistent, scale-invariant basis, contributing to the methodological robustness of the framework.

This study has limitations that point to valuable directions for future work. First, the framework relies on expert judgment for weighting and performance scoring, introducing subjectivity–though this is mitigated by BWM's consistency checks and aggregation across multiple experts. Second, the analysis operates at the strategic zonal level; it identifies where to invest first but not the exact street-level site. Future research should focus on integrating this MCDM framework with GIS-based spatial analysis to conduct micro-siting within the top-ranked zones identified here, as recommended in recent infrastructure prioritization literature [46]. Third, the framework should be tested and calibrated in other city types (e.g., North American sprawl, Asian megacities) to verify transferability and refine the criteria set. Fourth, a particularly promising direction is the incorporation of real-time and time-dependent mobility data — such as origin-destination flows derived from mobile network data, dynamic public transport occupancy, or seasonal shared vehicle usage patterns – into the scoring and weighting process. This would enable the framework to produce scenario-aware, temporally sensitive rankings that better reflect the evolving nature of urban mobility demand. A further valuable extension would be to combine this prioritization model with life-cycle cost analysis, creating a comprehensive tool that evaluates not only where and why to build, but also the full long-term economic and environmental costs of the investment [47].

By advancing in these directions, the methodology can evolve into an even more robust standard for the planning of next-generation urban mobility infrastructure—one that places analytical rigor at the service of more sustainable, equitable, and evidence-based cities.

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