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Mind the perception gap: Identifying differences in views among stakeholder groups of shared mobility services through bayesian best-worst method

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A R T I C L E   I N F O

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A B S T R A C T

This study investigates perception gaps among stakeholders—policy-makers, operators, users, and non-users—regarding car-sharing, bike-sharing, and scooter-sharing systems in Turin, Italy. Based on 628 surveys collected between November 2021 and February 2022 and analyzed using the Bayesian Best-Worst Method (BWM) multicriteria technique, it highlights key differences in prioritizing factors influencing shared mobility demand.

Key Findings: For car-sharing, policy-makers overestimate the importance of trip purpose compared to both users and non-users, while undervaluing service availability. Operators undervalue trip-related factors, such as travel time and departure time, while overemphasizing user-friendliness. For bike-sharing, policy-makers overestimate travel time compared to users while undervaluing travel comfort and environmental friendliness compared to both users and non-users. Operators underestimate trip-related factors, including travel distance and trip purpose, while overemphasizing environmental friendliness, particularly compared to non-users. For scooter-sharing, policy-makers underestimate trip-related characteristics, such as travel time and departure time, while overestimating travel cost and user-friendliness compared to non-users. Operators undervalue travel comfort and service availability, while overestimating travel distance, especially compared to users.

Managerial Insights: For car-sharing, policy-makers should expand service coverage and incentivize vehicle deployment, while operators should use dynamic fleet management and offer flexible booking options. For bike-sharing, policy-makers should subsidize fleet expansion and improve infrastructure, while operators should transition to free-floating models and integrate navigation tools. For scooter-sharing, policy-makers should enforce safety standards and improve accessibility, while operators should invest in high-quality scooters and adopt competitive pricing models.

Bridging these perception gaps is essential for fostering shared mobility adoption and enhancing user satisfaction.

1. Introduction and state of the art

In recent decades, changes have been seen in how urban transportation is viewed. Initially, the rising use of private transportation in industrialized countries provided greater access. However, it has led to negative externalities such as pollution and excessive energy

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and time consumption in the long run because of traffic congestion. This is more likely to occur mainly in urban areas where demand is concentrated during peak hours (Zhang et al., 2024). Furthermore, car ownership costs such as fuel, parking, and the cost of car insurance are rising (Mitchell et al., 2010; Berrill et al., 2024). Public transportation could be a proper alternative, but it has some limits. For example, public transport coverage does not provide door-to-door service, even in European cities with a significant public transport network, and it lacks personalization and a flexible schedule (Jorge and Correia, 2013). To complement public transport, shared mobility services can be helpful (Li, 2019). However, increasing the use of these types of services in society requires sufficient knowledge of factors affecting their demand from the perspective of different stakeholders, which may diverge. For instance, since car-sharing services are a mode of transportation that combines the advantages of private vehicles and transit services, transport policy-makers might not know how to consider these kinds of services. Nevertheless, the policy-makers role is central to promoting such services since they review operators' commitments through service contracts, manage political pressure, and provide rules for subsequent service deployment.

Although many policies promoting shared mobility use have been proposed, they have had a limited impact on triggering passengers to shift mode from private vehicles to shared mobility services. This might be because policy-makers and operators do not understand the real requirements of passengers for shared vehicles. In this regard, it is important to understand the different views of travelers, service providers, and policy-makers. Besides, the difference between the perspectives of users and non-users should be determined to strengthen users' habits and induce non-users to choose this service. Hence, it is necessary to identify the gap between the needs, expectations, and views of these four stakeholder groups related to shared mobility services. To do this, it is important to understand which factors influence their demand. Factors that could be important but whose impact on shared vehicles has not been well explored in the literature should also be considered.

Past studies provided partial evidence on the determinants of shared mobility demand. However, most focus on actual users, primarily investigating their socio-demographic characteristics. For example, some specific car-sharing services could attract more family members with children, people with a university education, single individuals (Carroll et al., 2017), or people aged between 25 and 54 with a higher household income (Ceccato, 2020). Further, Ceccato and Diana (Ceccato and Diana, 2021) worked on a multimodal perspective in studying car-sharing switching intentions in Turin, Italy. It was figured out that lower vehicle ownership levels could enhance demand for one-way station-based and free-floating car-sharing services. In more general terms, a comprehensive review of the effect of such sociodemographic factors on car usage can be found in (Amirnazmiafshar and Diana, 2022). Concerning bike-sharing and scooter-sharing, well-educated (Z. Chen et al., 2020; Laa and Leth, 2020) young adults (Eren and Uz, 2020; Rahimuddin, 2020) have a positive impression of such services. In addition, according to Shaheen and Cohen (Shaheen and Cohen, 2019), people who live in low-income households are interested in using scooter-sharing. Shaheen and Guzman (Shaheen and Guzman, 2011) stated that the bike-sharing program members (22 %) had higher car ownership rates than non-members (11 %) in Hangzhou, China, in 2010. While studies dealing with the individual profiles of users provide valuable insights into understanding the demand for such services beyond the specific study context, it should be noted that socio-demographic characteristics are not under the control of policy-makers and providers. Additionally, a systematic picture of different actors' viewpoints, beyond actual and potential users, is still missing for all shared mobility services (Eren and Uz, 2020; Politis et al., 2020; Mitra and Hess, 2021; Liao and Correia, 2022). Turning attention to other factors influencing shared vehicle demand, accessibility is an important one that should be considered (Eilertsen et al., 2024). In this regard, Juschten et al. (Juschten et al., 2017) indicated that increasing the number of stations within a 5 km radius of the household raises the likelihood of car-sharing membership in Switzerland. Similarly, accessibility is a significant factor in the demand for bike-sharing. Nearness to trails and agglomerations of hospitals, fast-food restaurants, offices, and clinics are influential environmental factors in cycling choices (Maurer, 2011). Regarding scooter-sharing, better access to transit is also positively associated with the increased use of e-scooters in Austin and Minneapolis, USA (Bai and Jiao, 2020).

Furthermore, characteristics associated with the trip can influence the demand (Eren and Uz, 2020). For instance, the departure time can remarkably affect the demand for shared mobility services. In this regard, Costain et al. (Costain et al., 2012) demonstrated that car-sharing systems are commonly used for travel during off-peak hours or weekends when transport services are insufficient and traffic is light. However, (Ji et al., 2020) found that the departure time in the morning rush hours (7am-9am) and the afternoon peak hours (5pm-7pm) is positively correlated to bike-sharing usage on workdays. Local factors are coming into play; for example, more considerable e-scooter traffic was observed in the afternoons and weekends in Austin, while Minneapolis experienced more evening riding and consistent daily vehicle miles traveled during the week (Bai and Jiao, 2020). Also, Jin et al. (Jin et al., 2020) pointed out that the trip purpose significantly impacted car-sharing usage and noted that users are more likely to utilize car-sharing for leisure trips than for commuting travels. Similarly, in Oslo, Norway, the two primary trip purposes of e-scooter users are leisure (40 %) and travel to/from school or work (29 %) (Berge, 2019). Also, Li and Kamargianni (Li and Kamargianni, 2018) noted that bike-sharing services are more likely to be selected for leisure trips than commuting trips.

Some other travel-related characteristics impact the use of shared vehicles. On this subject, Li (Li, 2019) stated that travel distance could significantly affect car-sharing usage. To increase car-sharing demand, policies should focus on saving users' travel time for longer trips and saving users' travel costs for short trips. The importance of this factor can also be seen in the demand for other shared transportation services. For example, in Berlin, Germany, e-scooters are mainly used for short distances, with an average distance of 1.54 km (Wüster et al., 2020). Also, there is a negative correlation between the bike-sharing ridership rate and the travel distance (between origin and destination) (El–Assi et al., 2017). Carroll et al. (Carroll et al., 2017) mentioned that shorter travel time could increase demand for round-trip car-sharing services. As well, shorter travel time can increase the demand for bike-sharing and scooter-sharing services (Ji et al., 2020; Younes et al., 2020).

Furthermore, factors related to service characteristics also impact the usage rate (Bai and Jiao, 2020). Quite predictably, lower travel costs can lead to higher usage. Also, some shared vehicle characteristics have been mentioned in the literature, even if their

Table 1
Studies focusing on different criteria and sub-criteria influencing the use of each shared mobility system.

Factors	Car-sharing	Bike-sharing	E-scooter-sharing
Travel time	(Cervero, 2003; Catalano et al., 2008; Efthymiou et al., 2013; Kim et al., 2017a; Carroll et al., 2017)	(Jensen et al., 2010; Buehler and Hamre, 2014; Mateo-Babiano et al., 2016)	(Berge, 2019; Clewlow, 2019; Todd et al., 2019; Younes et al., 2020)
Travel distance	(Martin and Shaheen, 2011; Costain et al., 2012; Wang et al., 2012; Martínez et al., 2017; Li, 2019)	(Fishman, 2016; Campbell et al., 2016; El–Assi et al., 2017; Li, 2019; Li et al., 2019; Ji et al., 2020; M. Chen et al., 2020)	(Smith and Schwieterman, 2018; Schellong et al., 2019; Todd et al., 2019; Wüster et al., 2020; Gössling, 2020)
Departure time	(Cervero, 2003; Costain et al., 2012; Ceccato, 2020)	(Froehlich et al., 2008; Kaltenbrunner et al., 2010; Kim et al., 2012; Faghih-Imani et al., 2014; O'brien et al., 2014; Corcoran et al., 2014; Reiss and Bogenberger, 2016; Ahillen et al., 2016; Mateo-Babiano et al., 2016; Kutela and Kidando, 2017; Kim, 2018; Heaney et al., 2019; Li et al., 2019; Ji et al., 2020; Lin et al., 2020)	(Mathew et al., 2019; Shaheen and Cohen, 2019; Younes et al., 2020; Bai and Jiao, 2020; Caspi et al., 2020)
Trip purpose	(Cervero, 2003; Martin and Shaheen, 2011; Le Vine et al., 2014; Kim et al., 2015; Cartenì et al., 2016; Wang et al., 2017; Le Vine and Polak, 2019; Jin et al., 2020)	(Fishman, 2016; Li and Kamargianni, 2018; Li, 2019; Noland et al., 2019; Li et al., 2019; M. Chen et al., 2020)	(Berge, 2019; Shaheen and Cohen, 2019; Noland, 2019; Caspi et al., 2020)
Travel cost	(Catalano et al., 2008; Shaheen and Martin, 2010; Lamberton and Rose, 2012; De Luca and Di Pace, 2015; Cartenì et al., 2016; Yoon et al., 2017; Carroll et al., 2017; Rotaris et al., 2019)	(Goodman and Cheshire, 2014; Fishman, 2016; Nikitas, 2018; Li and Kamargianni, 2018)	(Popov and Ravi, 2020; Bai and Jiao, 2020; Younes et al., 2020)
Travel comfort	(Schaefers, 2013)	(Zanotto, 2014; Leister et al., 2018)	(Sipe and Pojani, 2018; Schellong et al., 2019; Berge, 2019)
Service quality	–	–	(Popov and Ravi, 2020)
Service availability	(Cervero, 2003; Shaheen and Rodier, 2005; Millard-Ball, 2005; Burkhardt and Millard-Ball, 2006; Kortum, 2012; Habib et al., 2012; Kopp et al., 2015; Wagner et al., 2016; Juschten et al., 2017; Becker et al., 2017a; Dias et al., 2017; Namazu et al., 2018; Hu et al., 2018; Ceccato and Diana, 2021)	(Buck and Buehler, 2012; Kim et al., 2012; Hampshire and Marla, 2012; Bachand-Marleau et al., 2012; Croci and Rossi, 2014; Etienne and Latifa, 2014; Noland et al., 2016; Zhang, 2017; El–Assi et al., 2017; Kutela and Kidando, 2017; Duran-Rodas et al., 2019; Wang and Lindsey, 2019; Zhao et al., 2019; Lin et al., 2020; Ji et al., 2020)	(Zou et al., 2020; Katona and Juhasz, 2020; Bai and Jiao, 2020; Caspi et al., 2020)
Vehicle availability and accessibility	(Brook, 2004; Catalano et al., 2008; Stillwater et al., 2008; Zheng et al., 2009; Costain et al., 2012; Kim et al., 2017b; Juschten et al., 2017)	(Bachand-Marleau et al., 2012; Kim et al., 2012; Wang and Lindsey, 2019; Zhao et al., 2019; Ji et al., 2020)	(Bai and Jiao, 2020; Popov and Ravi, 2020)

impact on demand needs further investigation (Amirnazmiafshar, 2023). For instance, Schaefers (Schaefers, 2013) and Leister et al. (Leister et al., 2018) examined the impact of travel comfort on demand for car-sharing and bike-sharing, respectively. The importance of some other shared vehicle characteristics, including safety (Sun et al., 2021), service quality (Csonka and Csiszár, 2016; Popov and Ravi, 2020), environmental friendliness (Schulte and Voß, 2015; Popov and Ravi, 2020), and user-friendliness (Müller, 2019) have also been mentioned in the literature.

Last but not least, natural environmental conditions, including hilliness, weather conditions, temperature, seasonal effects, and pollution, can influence the demand for shared mobility services such as bike-sharing and e-scooter-sharing (Amirnazmiafshar, 2023). However, this study focuses on factors that can inform policies and operational strategies to attract users and non-users. As such, external environmental factors, while important, are not included in the analysis as they fall outside the scope of actionable interventions by stakeholders.

For a more comprehensive view, Table 1 lists some of the main factors influencing the use of each shared mobility system according to different authors, summarizing the complete literature review reported in Amirnazmiafshar (Amirnazmiafshar, 2023).

To summarize this review, the above factors can be classified into three groups. The first can be named trip-related characteristics, encompassing travel time, travel distance, departure time, and trip purpose. The second can cover travel mode characteristics, including travel cost and travel comfort. The third one includes availability and accessibility issues, including land use and the easiness of reaching a destination. Last but not least, an additional category would comprise the socio-demographic characteristics of the decision maker, including gender, age, occupation, economic status, vehicle ownership status, household size, marital status, presence

Table 2
Evaluation of MCDM methods (Amirnazmiafshar, 2023; Brispat, 2017).

MCDM	Year of development or method proposal	Transparency of the method	Required data	Quality of weights	Ability to combine with other methods	Avoid equalizing bias
ELECTRE	1966	Very negative	Neutral	Positive	Positive	Not available
WSM	1967	Very positive	Very positive	Not available or very negative	Very positive	Not available
WPM	1969	Very positive	Very positive	Not available or very negative	Very positive	Not available
AHP	1980	Neutral	Neutral	Positive	Neutral	Positive
TOPSIS	1981	Negative	Neutral	Not available or very negative	Not available or very negative	Not available
PROMETHEE	1985	Very negative	Neutral	Positive	Negative	Not available
BWM	2015	Neutral	Very positive	Very positive	Very positive	Positive

of children, and education level. However, as already mentioned, these are not under decision-makers' control and are therefore not considered in the following.

In this study, four stakeholders, including users, non-users, policy-makers, and operators, are compared in terms of their perception of the importance of each factor from the above three groups in attracting travel demand. This contributes to understanding how the perceptions of different car-sharing, bike-sharing, and scooter-sharing stakeholders can differ regarding specific factors. Based on this, suggestions can be given to operators and policy-makers to show how they should change their perspectives and priorities to grow the users' engagement and increase the attraction of non-users to services. The rest of the study explains the methodology applied in this study (Bayesian Best-Worst Method (Bayesian BWM)). Then, the data collection process is described, and the results and conclusions are delivered.

2. Method

Multi-criteria Decision Making (MCDM) methods are employed in this study. MCDM helps to estimate how a person makes decisions by considering multiple factors or criteria (quantitative and qualitative). Hence, unlike utility-based methods, it helps to incorporate the decision-makers preferences, including qualitative criteria. Furthermore, MCDM enables quantifying the relative importance of each criterion, providing a systematic approach to decision-making (Saaty and Ergu, 2015). Compared to econometric approaches that are customarily used, it is also possible to work with a very limited number of observations, which is a requirement given that we consider operators and decision-makers whose "universe" (in statistical terms) is made by only a few individuals.

Specific MCDM methods are selected based on their specific features and diffusion across the relevant literature. Comparative studies include the works of Triantaphyllou (Triantaphyllou, 2000), Mulliner et al. (Mulliner et al., 2016), Kolios et al. (Kolios et al., 2016), and Serrai et al. (Serrai et al., 2017). Furthermore, Yannis et al. (Yannis et al., 2020) notably highlighted the dominant usage of specific MCDM techniques in transportation. Their research revealed that almost 29 % of studies in this field employed the Analytic Hierarchy Process method. Collectively, methods such as the Elimination and Choice Translating Reality, Weighted Sum Model, Weighted Product Model, Analytic Hierarchy Process, Technique for Order of Preference by Similarity to Ideal Solution, Preference ranking organization, and the BWM cover a significant 71 % of the MCDM methods applied.

Compared to the methods mentioned above, BWM was selected for this study due to its specific advantages, including its innovative reference-based pairwise comparison approach, reduced cognitive load, and enhanced consistency of results. Unlike the Analytical Hierarchical Process (AHP), which demands a comprehensive suite of pairwise comparisons, BWM requires a minimal set of these, specifically the so-called reference pairwise comparisons (Liang et al., 2020; Yang and Wu, 2023). BWM requires only $2n-3$ comparisons compared to $\frac{n\,(n-1)}{2}$ required by AHP, making it significantly more efficient (Liang et al., 2020). Moreover, the inherent structure of BWM, characterized by two vectors composed exclusively of integers, bypasses the inherent complications associated with fractional pairwise comparisons, as detailed by Salo and Hämäläinen (Salo and Hämäläinen, 1997). This unique structure also reduces inconsistencies in pairwise comparisons, enhancing the reliability of the results. To evaluate MCDM methods, Table 2 summarizes their benefits, drawbacks, and features according to the literature (Amirnazmiafshar, 2023; Brispat, 2017).

Coming to practical considerations, BWM's design and methodology offer both ease of application and clarity of understanding. Both substantial advantages are its ability to facilitate structured comparisons and produce reliable weights. When considering its wide-ranging applicability across different MCDM problems, including those involving both quantitative and qualitative criteria, the merits of BWM stand out clearly (Gu et al., 2023). Brispat (Brispat, 2017) offers a more comprehensive analysis of the value of the above methodologies, particularly emphasizing the significance and advantages of the BWM. Thus, the practical advantages of BWM can be summarized as follows:

- Reduced Cognitive Load: BWM requires fewer pairwise comparisons, making it less burdensome for respondents while maintaining methodological rigor.
- Consistency of Results: BWM generates weights with fewer inconsistencies, ensuring more reliable rankings compared to other methods.
- Avoidance of Equalizing Bias: BWM minimizes the tendency of decision-makers to assign nearly equal weights to all criteria.

- Efficient Data Requirements: The method performs well even with limited datasets, making it suitable for studies with specialized stakeholder groups.
- Wide Applicability: BWM is compatible with various decision-making scenarios, including those with both quantitative and qualitative criteria.

In this study, Bayesian BWM was employed to further enhance the robustness of the analysis. Bayesian BWM incorporates probabilistic models, allowing for additional insights such as credal rankings and confidence levels in weight-directed graphs. These features provide a deeper understanding of stakeholders' priorities and the relative importance of criteria.

To conclude, BWM was chosen for its ability to generate consistent and reliable weights with limited data, its reduced computational burden compared to traditional methods like AHP, and its superior performance in avoiding bias. These strengths make BWM particularly suitable for evaluating stakeholder perceptions in shared mobility systems.

In the application of the BWM in this study, the following steps are taken (Rezaei, 2015; Rezaei, 2016):

Step 1: Definition of the decision criteria. Decision-making criteria are established, with respondents presented with criteria to be ranked.

Step 2: Determine the best and the worst criteria. Respondents select the most (best) and least (worst) significant criteria from the given set.

Step 3: Determine preference of best criterion over other criteria. Using a scale of one to nine, respondents indicate the strength of their preference for the best criterion compared to the others. A 'one' score denotes an equal preference, while a 'nine' score implies an extreme preference for the best criterion.

Step 4: Determine the preference of other criteria over the worst criterion. Respondents use the same scale of step 3 to signify the preference of all other criteria over the designated worst criterion.

Step 5: Find the optimal weights. After data collection, the criteria' optimal weights are computed.

When aggregating the preferences of multiple respondents, traditional methods might inaccurately represent collective preferences due to outliers. This study uses the Bayesian BWM to overcome this. In this variant, weights are not simply derived and averaged in step 5, but a probabilistic model is set up, simultaneously determining collective and individual preference distributions. Additionally, the input-based approach can check the consistency of the responses. This method, therefore, offers an accurate representation of group decisions, as pointed out by Mohammadi and Rezaei (Mohammadi and Rezaei, 2020) and Kalpoe (Kalpoe, 2020).

Therefore, the decision to utilize Bayesian BWM in this study is rooted in its ability to accommodate diverse stakeholder groups. One of its standout features allows for a preliminary assessment of respondent consistency before determining optimal group weights. Only those pairwise comparisons meeting the benchmark of acceptable consistency ratios are considered (Liang et al., 2020). Beyond this, the Bayesian BWM model provides a deeper and more comprehensive layer of understanding (Ma et al., 2019). By offering both a credal ranking and a confidence level within the weight-directed graph, as later detailed when presenting the method, it presents a nuanced view into how stakeholders perceive the relative importance of one criterion over another, delivering additional insights for our analysis.

To summarize the main points of the above discussion, Bayesian BWM requires a small amount of data compared to more traditional approaches such as AHP, Ideal Solution (TOPSIS), Preference Ranking for Organization Method for Enrichment Evaluation (PROMETHEE), and Elimination and Choice Translating Reality (ELECTRE) (Brispat, 2017). In addition, compared to other multi-criteria analysis methods, additional advantages include fewer inconsistencies between criteria, lower equalizing bias (Rezaei et al., 2022), and better transparency for decision-makers compared to PROMETHEE, ELECTRE, and TOPSIS (Brispat, 2017; Rezaei, 2016). Therefore, in this study, Bayesian BWM will be used to calculate the aggregatefinal criteria weights for a group of stakeholders at once. The above steps, 1 to 4, are related to field activities and will be later illustrated in the Data section. Therefore, the remainder of this section focuses on step 5, where the first task is examining the consistency of the respondents using the Input-based approach.

2.1. Input-based approach

Consider a set of n evaluation criteria indexed *j, j* = 1, …, n. CR^I is defined as the global Input-based consistency ratio for all criteria as follows (Liang et al., 2020):

$$\mathrm{CR}^I = \max_j CR_j^I \tag{1}$$

Where

$$CR_j^I = \begin{cases} \frac{\left| a_{Bj} \times a_{jW} - a_{BW} \right|}{a_{BW} \times a_{BW} - a_{BW}} & a_{BW} > 1 \\ 0 & a_{BW} = 1 \end{cases} \tag{2}$$

In turn, CR_j^I indicates the local consistency level associated with the criterion C_j. Then, a_{Bj} shows the preference for the best criterion C_B over criterion C_j, a_{jW} represents the preference for criterion C_j over the worst criterion C_W, and a_{BW} indicates the preference for the best criterion over the worst criterion. Such preferences are expressed through semantic scales ranging from 1 to m, where 1 means that the two criteria under consideration are deemed equally important, m indicates an extreme preference of one over the other, and 2, …, m - 1 are intermediate cases. Typically, m = 9 in BWM, although a different number of points could also be

Table 3
CR^I thresholds based on the number of criteria and a_{BW} (Liang et al., 2020).

	Number of criteria						
	3	4	5	6	7	8	9
3	0.1667	0.1667	0.1667	0.1667	0.1667	0.1667	0.1667
4	0.1121	0.1529	0.1898	0.2206	0.2527	0.2577	0.2683
5	0.1354	0.1994	0.2306	0.2546	0.2716	0.2844	0.2960
6	0.1330	0.1990	0.2643	0.3044	0.3144	0.3221	0.3262
7	0.1294	0.2457	0.2819	0.3029	0.3144	0.3251	0.3403
8	0.1309	0.2521	0.2958	0.3154	0.3408	0.3620	0.3657
9	0.1359	0.2681	0.3062	0.3337	0.3517	0.3620	0.3662

used. Additionally, a_{BW} should be larger than 2 (for more details: (Liang et al., 2020)), hence, a_{BW} ranges from 3 to 9.Consistency ratio thresholds are then derived to assess whether respondents gave sufficiently consistent responses, following the computations detailed in (Liang et al., 2020) that consider up to 9 different criteria since people cannot effectively compare >9 criteria at the same time. As a result, the CR^I thresholds according to the number of criteria n and the above-introduced preference of best over worst criterion (a_{BW}) are listed in Table 3. The CR^I values below these thresholds are deemed acceptable. As shown in the columns of Table 3, the number of criteria that are jointly considered varies from 3 to 9 since there are no consistency issues for less than three criteria.

Before employing Bayesian BWM for optimal group weight calculation, respondent consistency using the Input-based approach was assessed, and the responses to the BWM questions that did not meet the requisite consistency standards were excluded for data quality assurance. Only those with a global input-based consistency ratio (CR^I) below the specified thresholds (refer to Table 3) were retained (Liang et al., 2020). However, the present study considers a two-level analysis, following the literature review findings in Table 1 (the final criteria are presented in Table 5). Sometimes, respondents provided consistent answers only in one of the two levels: in this case, their data was used for that level's analysis, as done, for example, by Kalpoe (Kalpoe, 2020). This process resulted in varying sample sizes across different model levels due to the removal of pairwise comparisons with unsatisfactory consistency ratios.

2.2. Optimal weights computation

Optimal weights for stakeholders are evaluated through the joint probability of the group decision, as shown in Eq. (3) (Mohammadi and Rezaei, 2020), only considering those answers that were positively evaluated through the above-introduced Input-based approach:

$$P\left(w^{agg},\ w^{1:K} \middle| \ A_B^{1:K},\ A_W^{1:K} \right) \propto P\left(A_B^{1:K},\ A_W^{1:K} \middle| \ w^{agg},\ w^{1:K} \right) P\left(w^{agg},\ w^{1:K}\right)$$
$$= P(w^{agg}) \prod_{k=1}^{K} \mathrm{P}\left(A_W^k \middle| w^k \right) \mathrm{P}\left(A_B^k \middle| w^k \right) \mathrm{P}\left(w^k \middle| w^{agg} \right) \tag{3}$$

Where:

- $P(\ w^{agg},\ w^{1:K} |\ A_B^{1:K},\ A_W^{1:K})$: the joint probability of the group decision for the Bayesian BWM
- A_B^k: vector of preferences of the best criterion over other criteria (BO vector) of the k-th decision-maker
- A_W^k: vector of preferences of all criteria over the worst criterion (OW vector) of the k-th decision-maker
- $A_B^{1:K}$: BO vectors of all K decision-makers
- $A_W^{1:K}$: OW vector of all K decision-makers
- w^k: optimal weights of the k-th decision-maker
- $w^{1:K}$: optimal weights of all K decision-makers
- w^{agg}: aggregated weight (optimal group weight after aggregation).

Eq. (3) is achieved utilizing various variables' probability chain rule and conditional independence, and each decision-maker independently presents the preferences. It is important to note that this study assumes that the criteria have no interdependencies. The latter seems a reasonable assumption when considering the criteria that will be later introduced (see Table 5) as they are exploring different cognitive dimensions that can influence the decision-making process, with the possible partial exception of sub-criteria C3.1 and C3.2. This latter case, however, does not prejudice the general validity of the interdependency assumption, which is routinely considered in MCDM studies.

In the Bayesian BWM, the criteria can be compared through credal ranking, an approach for probabilistic comparison of a set of criteria that can be visualized utilizing directed graphs. The nodes are the criteria, and the directed edges connecting two nodes show which of the two criteria is more important than the other (Mohammadi and Rezaei, 2020). Edges in the graph have an attribute called "confidence d" or "confidence level" (CL), which is basically the extent to which one can claim one criterion is more important than the other. This comes from the probabilistic nature of the model. The expression "confidence d" was presented in the main article in which the Bayesian BWM was introduced (Mohammadi and Rezaei, 2020), whereas recent literature (Kalpoe, 2020) uses

Table 4
Description of each CL range for a threshold value of 0.50 (Amirnazmiafshar and Diana, 2023).

CL range	Description
CL ≥ 0.80	One criterion is certainly more important than the other
0.60 ≤ CL < 0.80	One criterion is more important than another
0.50 ≤ CL < 0.60	The superiority of one criterion over another is not well-established

the term "confidence level". This study uses the latter expression, which should not be confounded with the confidence level concept in statistics.

The interested reader is referred to (Mohammadi and Rezaei, 2020) for additional technical details on credal ranking. The closer the Confidence Level (CL) is to 1, the more pronounced the degree of certainty about the relation, indicating that one criterion is certainly considered more important than another (Mohammadi and Rezaei, 2020). It is important to note that the credal ranking can be changed into the conventional ranking merely by applying the threshold of 0.5 to the obtained confidence. However, the threshold can vary from problem to problem, and choosing a particular threshold value is entirely up to the decision-maker. In other words, credal ranking can be shaped to show criteria ranking in various problems based on the confidence desired by decision-makers (Mohammadi and Rezaei, 2020). There is no specific classification to describe CL in the literature. Hence, this study intends to introduce the CL classification to explain the results in line with previous studies (Kalpoe, 2020; Mohammadi and Rezaei, 2020; Amirnazmiafshar and Diana, 2023). In this regard, Table 4 describes each CL range with a threshold value 0.5. It should be noted that when the threshold value is 0.5, values <0.5 are not considered in this classification because values <0.5 (CL<0.5) must be interpreted inversely. For instance, when the confidence level for comparing C1 and C2 is 0.30, C2 is more important than C1, with a confidence of 0.7 (i.e., 1 – 0.3 = 0.7).

It is important to note that if the number of criteria is more than nine, they can be classified into different groups because, in general, humans can only compare up to nine attributes (Glassman et al., 1994). In that case, there are main-criteria and their sub-criteria (sub-factors). Weights obtained for the sub-criteria of the BWM are called local weights. The local weights can only be utilized to compare the importance of sub-criteria (sub-factors) belonging to the same main-criterion (factors). For each sub-criterion, the global weight can then be computed by multiplying each local weight of the sub-criterion by the weight of its respective main-criterion. These weights are called 'global weights' because they can be compared in importance, regardless of the classification (main-criteria) to which they belong.

It is finally important to note that the use of Bayesian BWM makes it possible to understand the importance perceived by stakeholders of one criterion over other criteria since this method can provide the credal ranking and CL in the weight-directed graph (Mohammadi and Rezaei, 2020; Wang et al., 2023). To the authors' knowledge, Bayesian BWM has never been used to characterize the demand for shared mobility services, especially to find gaps in the perceptions of different car-sharing, bike-sharing, and scooter-sharing stakeholders. This study uses the MATLAB implementation of Bayesian BWM introduced by Mohammadi and Rezaei (Mohammadi and Rezaei, 2020) to compute the weights and plot credal ranking graphs.

3. Field activities and data treatment

To gather data, surveys were conducted between November 2021 and February 2022 in Turin, Italy. Turin is one of the Italian cities where various shared services have been developed. Turin has established a comprehensive shared mobility ecosystem encompassing car-sharing, bike-sharing, and e-scooter services. Active car-sharing operators include Enjoy, Share Now, and Drivalia, offering both free-floating and station-based rental models. In the bike-sharing sector, free-floating services are provided by operators such as Bolt, Lime, and RideMovi. E-scooter sharing is facilitated by companies including Bird, Bolt, Dott, Helbiz, Lime, Link, and Voi, all operating on a free-floating basis (Muoversi a Torino, n.d.). This diverse array of shared mobility options underscores Turin's commitment to sustainable and flexible urban transportation solutions. Hence, it is a suitable case study. Members of all the above four stakeholder groups were asked to answer surveys and rank criteria. However, surveying strategies had to be adapted according to the specific group under consideration. Regarding users and non-users, the survey was administered online through a market research panel of respondents to achieve good representativeness of these two groups in the study area in terms of standard socio-demographic characteristics. In fact, the usual sampling theory applies in this case, and the goal is to get statistically significant results for the entire population of users and non-users in the study area. In total, 76 responses were collected from car-sharing users, 126 from car-sharing non-users, 75 from bike-sharing users, 127 from bike-sharing non-users, 77 from scooter-sharing users, and 126 from scooter-sharing non-users. This resulted in 607 valid responses from users and non-users across the three shared mobility services.

The same approach clearly does not work when considering either operators or policy-makers. Data were collected through phone calls to targeted contact points in these cases. These groups are, in fact, formed by a very small number of individuals, each covering a specific and often unique role in their respective organization, so nobody can be considered representative of the whole group, and even the statistical concept of the sample seems hardly appropriate. For operators and policymakers, three responses were collected from car-sharing operators and four from policymakers; three responses were collected from bike-sharing operators and five from policymakers; and three responses were collected from scooter-sharing operators and three from policymakers. This resulted in a total of 21 valid responses across operators and policymakers. Altogether, the study included a total of 628 responses: 607 from users and non-users and 21 from operators and policymakers.

Table 5
List of main-criteria and sub-criteria and definition of sub-criteria.

Main-criteria and sub-criteria	Definition of sub-criteria
C1. Trip-related characteristics	
C1.1. Travel time	The time it takes with a shared vehicle to travel from origin to destination.
C1.2. Travel distance	The distance between the origin and destination
C1.3. Departure time	The trip's start time, such as in the morning or evening, on weekends or weekdays, during peak or off-peak hours
C1.4. Trip purpose	The purpose of the trip, such as traveling to work, school, shopping, or meeting a friend
C2. Shared vehicle characteristics	
C2.1. Travel cost	Expenses for each shared mobility service usage (e.g., service subscription fees or usage fees)
C2.2. Travel comfort	Vehicle characteristics that make passengers feel comfortable during the trip
C2.3. Safety	The level of safety of the individual during the trip, such as the rate of accidents, harassment, assault, and theft
C2.4. Service quality	Quality of shared mobility service
C2.5. Environment-friendly system	A system that reduces environmental impacts
C2.6. User-friendly	Easy for beginners to learn, easy to use, and provide travel information in the app
C3. Availability and accessibility	
C3.1. Service availability	Availability of shared mobility services around shopping malls, colleges, transportation centers, city centers, and densely populated areas
C3.2. Vehicle availability and accessibility	Availability of the vehicle where it is needed, easiness of reaching and accessing the vehicle, proximity to the location of the parked vehicle from the passenger's starting point

In general terms, decisions result from a collective process in which individual roles change from one organization to another. It is generally possible to distinguish between two levels, namely a technical level that provides information to a management or policy level in charge of the final decision. However, it is not easy to understand where the decision power is in practice. In some cases, the policy level could be making decisions irrespective of technical analyses (too often in the transport sector). At the other extreme, the management could ratify the technical analysis output and related assumptions and views (leading to a technocratic approach).

In principle, a detailed analysis of the dynamics of decision-making processes related to these services within both the operators and public bodies in the study area would be needed to understand the role of each individual and, therefore, accurately represent the viewpoint of the specific group.

Questions for operators and policymakers focused on decision-making criteria such as service quality, safety, and accessibility and their opinions on characteristics influencing user adoption (e.g., service availability and environmental friendliness). On the other hand, surveys for users and non-users included two types of questions: one set focused on assessing the importance of specific criteria (e.g., travel cost, safety, accessibility), and another on contextual insights, such as daily travel routines and socio-demographic characteristics. While these contextual questions provided valuable background, they were not the primary focus of this study. Additional information on the specific role of each survey respondent within their respective organization can be found in Amirnazmiafshar (Amirnazmiafshar, 2023). However, here, we are rather interested in analyzing differences among groups. On the other hand, it is likely that individual views inside a given operator or local administration are not radically diverging, irrespective of roles. Taking this assumption, answers were elicited from operators and policy-makers representatives in general.

In light of the previous discussion and as later shown, the number of interviews for those two groups is very low since the concept of a statistical sample is not applied here. Since Bayesian BWM is relatively new, published research involving key decision makers rather than more generic people is relatively scarce, and related experimental practices are not yet consolidated. However, it is noted, for example, that Brispat (Brispat, 2017) considers only 15 passengers, and in a study by Praditya and Janssen (Praditya and Janssen, 2017), there were only four respondents, while Stević et al. (Stević et al., 2018) used only seven respondents.

Operators of each shared mobility service answered questions related to the kind of service they run. However, policy-makers randomly answered one survey related to car-sharing, bike-sharing, or scooter-sharing. Details on the design of the different surveys (by stakeholder and by mobility service) and their implementation can be found in Amirnazmiafshar (Amirnazmiafshar, 2023). The following presents the service evaluation criteria that the respondents assessed.

As the methodology mentions, a set of decision criteria must first be determined. Based on the literature review sketched in the introduction, twelve different sub-criteria have been identified as having an important effect on car-sharing, bike-sharing, and scooter-sharing demand. These, in turn, can be grouped into the three above-mentioned main-criteria: trip-related, shared vehicle characteristics, and availability and accessibility characteristics. Both the main-criteria and the related sub-criteria are presented in Table 5. As explained in the introduction, socio-demographic characteristics are not considered in this framework, even if they play a role in shaping demand.

Interviewees had to choose the most important and least important sub-criteria within each main-criterion when considering the role of such criteria in influencing the choice to use the shared mobility service under consideration. In other words, operators and policy-makers responded based on their understanding of the general public's views concerning specific factors rather than expressing their personal opinions. They addressed questions like: "Based on your understanding, which trip-related characteristic (from travel time, travel distance, departure time, and trip purpose) do you think is the MOST IMPORTANT and the LEAST IMPORTANT for individuals when considering car-sharing for a trip?". Conversely, the general public, both users and non-users of the service, answered similar questions based on their personal experiences and preferences. For example, they were asked: "For you personally, which of the following characteristics - travel time, travel distance, departure time, or trip purpose - is the MOST IMPORTANT and the LEAST IMPORTANT if you were supposed to decide to use car-sharing for a trip?".

Table 6
Number of responses that were considered from each stakeholder for the main-criteria and each sub-criteria set for each type of shared mobility service.

Shared vehicle service type	Type of stakeholder	Main-criteria set	Sub-criteria sets			Original sample size
			Trip-related characteristics	Shared vehicle characteristics	Availability and accessibility	
Car-sharing	**Users**	15	39	36	39	76
	Non-users	24	59	56	59	126
	Operators	2	3	3	3	3
	Policy-makers	2	3	4	4	4
Bike-sharing	**Users**	18	38	37	38	75
	Non-users	32	69	63	69	127
	Operators	2	3	3	3	3
	Policy-makers	2	4	4	4	5
Scooter-sharing	**Users**	13	42	37	42	77
	Non-users	24	66	48	66	126
	Operators	1	3	3	3	3
	Policy-makers	2	3	3	3	3

Main-criteria and sub-criteria were the same for all, as shown in Table 5, irrespective of the stakeholder group to which the interviewees belonged. Then, they rated how much they prefer the chosen most important sub-criterion over other sub-criteria through a semantic scale ranging from 1 to 9, where one means equal importance and nine means extremely more important. Similarly, they rated the degree to which the other sub-criteria are preferred over the chosen least important sub-criterion. The same exercise is separately done for the three sub-criteria within each main-criterion. Finally, the main-criteria (C1, C2, and C3) were rated similarly.

The Input-based approach was then used to check for the consistency of the answers, according to the above-introduced process. After eliminating the responses that have pairwise comparisons with unacceptable consistency ratios, different sample sizes can be obtained and utilized for different levels of the model. The number of responses considered for the main criteria and each sub-criteria set for each stakeholder of each shared mobility service is shown in Table 6, along with the number of answers gathered from the survey in the last column.

In the main-criteria C3 (availability and accessibility), there are only two sub-criteria: C3.1 (service availability) and C3.2 (vehicle availability and accessibility). Therefore, user respondents would never make the error of incorrectly assigning the highest value to the best-worst vector, and all survey answers are, in principle, valid. However, the last two columns in the table (i.e., those pertaining respectively to C3 and the original sample size) do not show the same numbers for each shared service/stakeholder combination because, for C3, we only considered the same set of valid answers from the largest set between C1 (trip-related characteristics) and C2 (shared vehicle characteristics). Consequently, the second to last column reports a sample size that is the largest between those in columns 4 and 5 in the table. This cautionary approach aims to consider only data from respondents who have made accurate pairwise comparisons. Finally, it can be seen that the number of responses retained for the main criteria set (third column of Table 6) is much smaller compared to the number of responses considered for the three sub-criteria sets (columns 4 to 6). This happens because the main criteria are three, compared to four sub-criteria for C1 and six for C2; therefore, the corresponding thresholds are much lower, leading to higher rejection rates, as apparent when comparing the threshold values in the second column of Table 3 with the values in the remaining columns of the same table.

4. Results

The main output of the analysis is given by the group weights (global weights) and the credal rankings of the three main-criteria and the twelve sub-criteria for each stakeholder group and each kind of shared service. This output is presented in Figs. 1 to 5.

Fig. 1 indicates the weight of the three main-criteria corresponding to each stakeholder of each shared mobility service. In addition, information on the strength of the important relationship is conveyed by considering the confidence level ranges shown in Table 4: appropriate symbols are added on top of the different bars. To introduce such symbols, let C^H, C^L, and $C^M \in$ {C1, C2, C3} be the main-criterion, respectively, having the highest, lowest, and medium weight when considering a specific shared service and a specific stakeholder. Also, let $CL_{H,M}$ indicate the confidence level of the edge connecting C^H and C^M in the corresponding credal ranking graph, while $CL_{M,L}$ is the confidence level of the edge between C^M and C^L, and $CL_{H,L}$ is the confidence level of the edge between C^H and C^L. There are $3 \times 4 = 12$ possible combinations of shared service and stakeholder. The twelve C^H, C^M, and C^L triplets correspond to twelve credal ranking graphs with their confidence levels. Then, all bars of Fig. 1 whose length represents the weight of C^H show a symbol on their top according to the following legend:

- "***" if $CL_{H,M} \geq 0.80$ and $CL_{H,L} \geq 0.80$;
- "**" if $0.60 \leq CL_{H,M} < 0.80$ and $CL_{H,L} \geq 0.80$;
- "*" if $0.60 \leq CL_{H,M} < 0.80$ and $0.60 \leq CL_{H,L} < 0.80$;
- "++" if $50 \leq CL_{H,M} < 0.60$ and $CL_{H,L} \geq 0.80$;
- "+" if $50 \leq CL_{H,M} < 0.60$ and $0.60 \leq CL_{H,L} < 0.80$;
- ".", if $50 \leq CL_{H,M} < 0.60$ and $50 \leq CL_{H,L} < 0.60$.

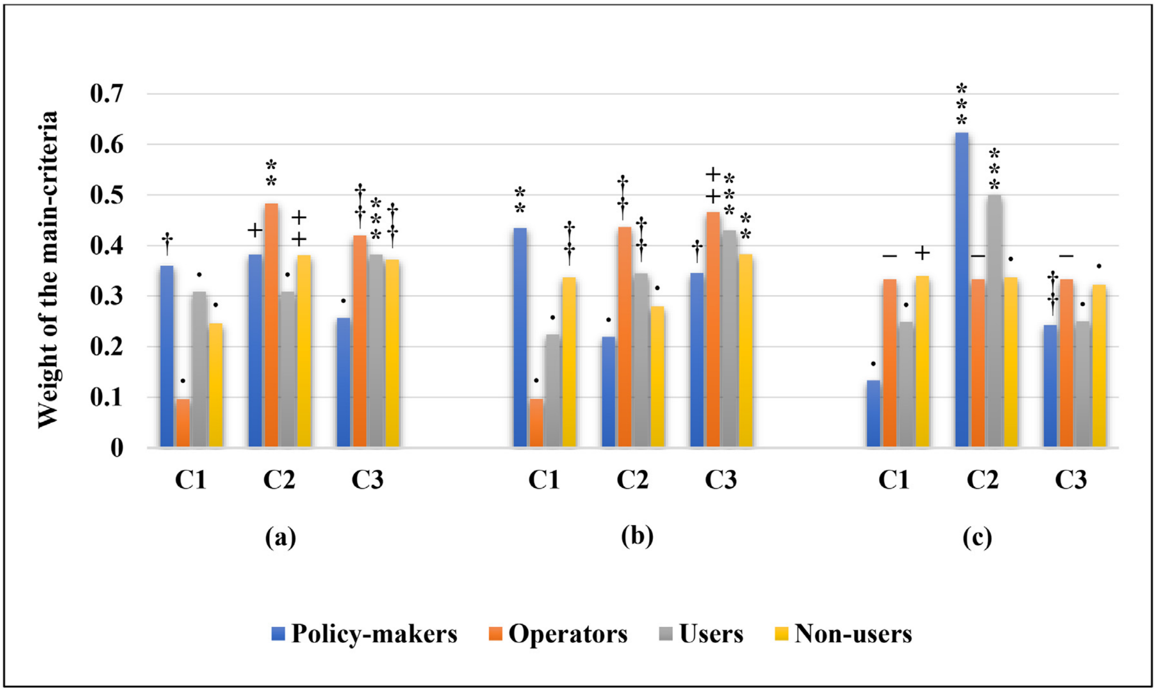

Fig. 1. The weight of the main-criteria corresponding to stakeholders for car-sharing (a), bike-sharing (b), and scooter-sharing (c).

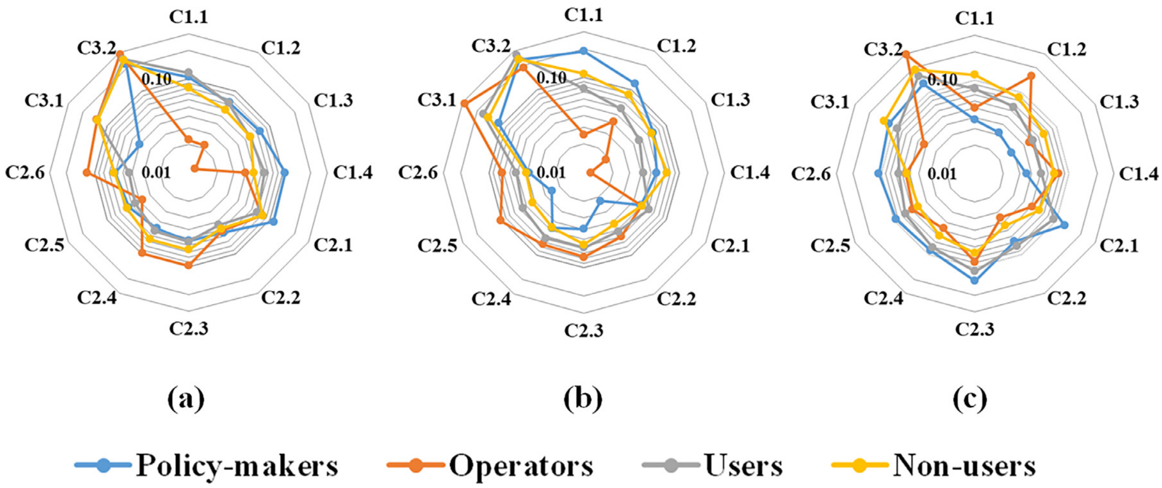

Fig. 2. The weight of the sub-criteria (on a logarithmic scale) corresponding to stakeholders of car-sharing (a), bike-sharing (b), and scooter-sharing (c).

Similarly, all bars in Fig. 1 related to C^M show a symbol according to this legend:

- "††" if $CL_{M,L} \geq 0.80$;
- "†" if $0.60 \leq CL_{M,L} < 0.80$;
- ".", if $50 \leq CL_{M,L} < 0.60$

Finally, all bars in Fig. 1 related to C^L have a point "." symbol. It should also be mentioned that confidence levels could not be assessed for scooter-sharing operators. The reason is that only one scooter-sharing operator's response (out of the three answers) was considered when dealing with the main-criteria, as shown in Table 6. Therefore, a "–" symbol is reported on the corresponding bars.

Concerning sub-criteria, Fig. 2 shows their weights (a logarithmic scale has been used to have a better view) corresponding to each stakeholder of car-sharing, bike-sharing, and scooter-sharing, respectively. Web graphs are used to give a better overview of which groups of sub-criteria are deemed relatively more or less important by different stakeholders for each service. Finally, Figs. 3–5 represent the credal ranking graphs of sub-criteria and their respective confidence levels for the three systems to understand the

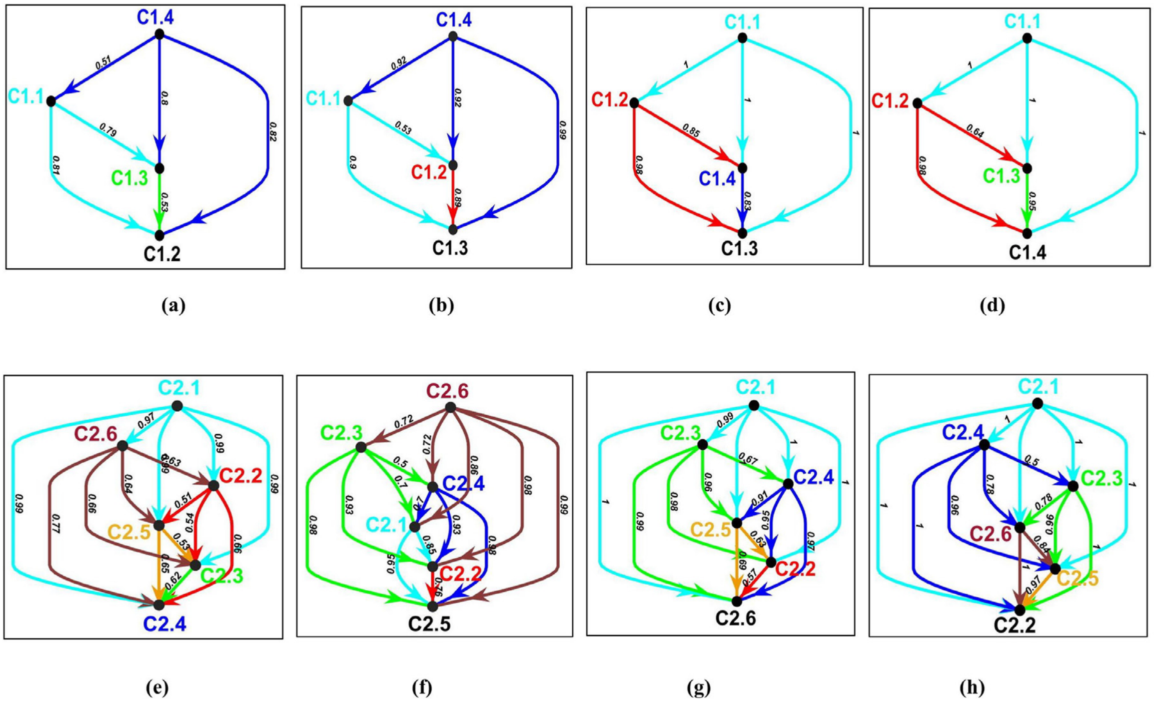

Fig. 3. Credal ranking of sub-criteria belonging to the main-criteria C1 (a) and C2 (e) from the policy-makers view, C1 (b) and C2 (f) from operators' perspectives, C1 (c) and C2 (g) from users standpoint and C1 (d) and C2 (h) from non-users viewpoint of car-sharing service.

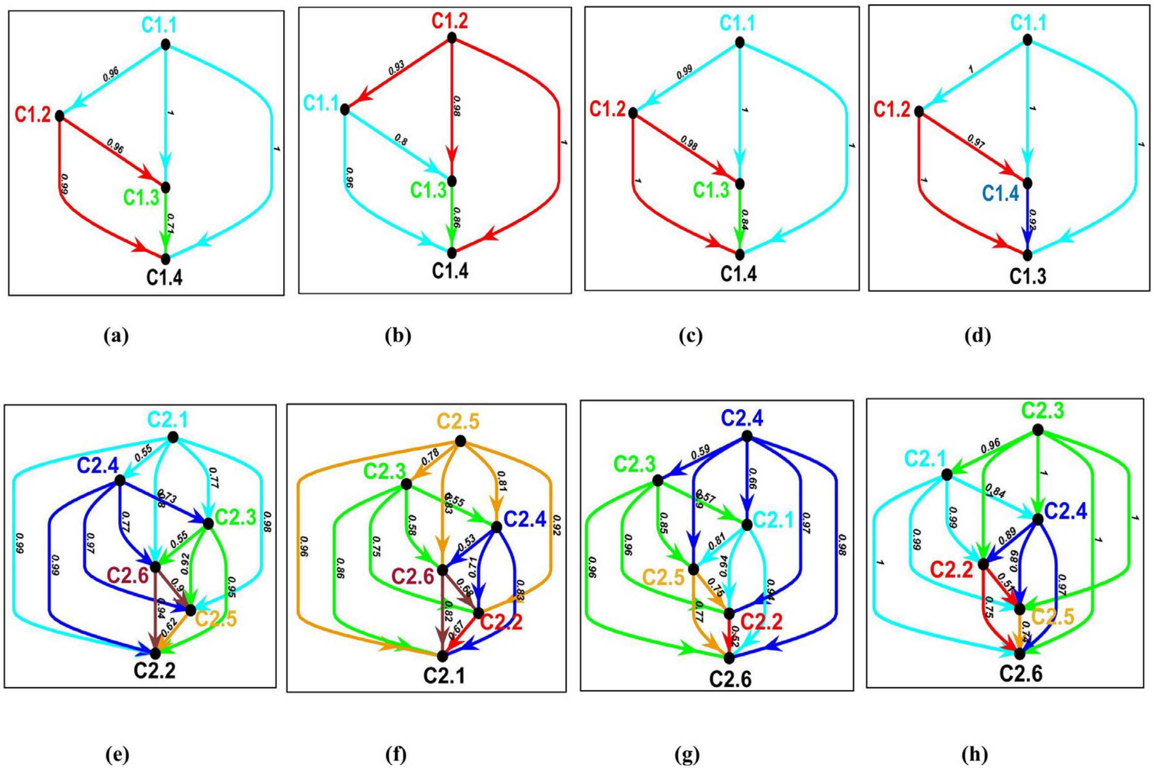

Fig. 4. Credal ranking of sub-criteria belonging to the main-criteria C1 (a) and C2 (e) from the policy-makers view, C1 (b) and C2 (f) from operators' perspectives, C1 (c) and C2 (g) from users standpoint and C1 (d) and C2 (h) from non-users viewpoint of bike-sharing service.

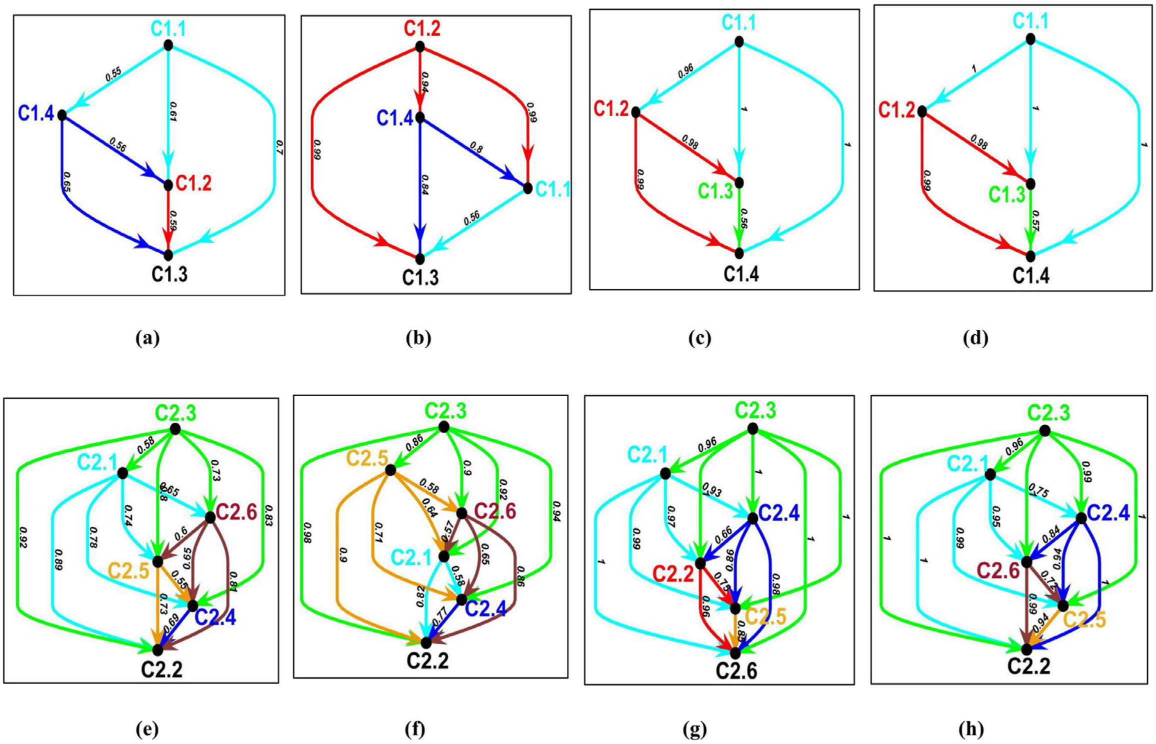

Fig. 5. Credal ranking of sub-criteria belonging to the main-criteria C1 (a) and C2 (e) from the policy-makers view, C1 (b) and C2 (f) from operators' perspectives, C1 (c) and C2 (g) from users standpoint and C1 (d) and C2 (h) from non-users viewpoint of scooter-sharing service.

strength of the different relationships. Only graphs related to C1 and C2 sub-criteria are shown since only two sub-criteria exist for C3; therefore, the corresponding graph collapses to one edge with two nodes. Concerning the latter, it can be synthetically reported that sub-criterion C3.2 is definitely more important than C3.1 for all the considered stakeholders, except for policy-makers of scooter-sharing services, where such a relationship is fading (CL = 0.56) and for operators of bike-sharing who, on the contrary, believe that C3.1 is more important than sub-criterion C3.2.

Jointly considered, the above plots represent a complete but compact way to report all results while easing their interpretation through visualization. Many different patterns emerge: instead of systematically describing what can be directly observed in each plot, a more complete and synthetic description of the specific views of different operators is reported in the following three subsections. It is provided according to the main-criteria and sub-criteria for each shared mobility service, and it considers both operators' views concerning the relative importance of all criteria and the importance rankings of the three main-criteria and the different sub-criteria within each main-criterion. Finally, subSection 4.4 explicitly identifies the main perception gaps between policy-makers and operators on the one hand and both users and non-users on the other.

To correctly interpret the results, it is important to constantly recall that importance assessments of different criteria were not elicited in generic terms but by asking the respondent to consider the role of each criterion in improving the attractiveness of a given service. Therefore, a stakeholder indicating that a given criterion (for example, environmental concerns) is relatively less important to increase the choice probabilities of a given service does not necessarily imply that s/he believes that such criterion is less important per se.

4.1. Car-sharing stakeholders' views and criteria rankings

It can be noted that when policy-makers or operators consider a factor/sub-factor as "less important" or "more important" than another, they might be influenced by their professional perspective on the extent to which they can control such a factor. However, we reiterate here that they were required to assess the importance of each factor for travelers, as mentioned above, when the survey questions were administered, and we, therefore, accordingly interpret the analysis results. Concerning car-sharing services, Fig. 1(a) illustrates that availability and accessibility (C3) is less important than the other two criteria for policy-makers to attract customers. In contrast, trip-related characteristics (C1) are largely less important than C2 and C3, according to service operators. In line with the previous remark, operators probably tend to consider travel demand characteristics as exogenous in the traveler decision-making process, not enough thinking about their implications in the service use, while policy-makers should pay more attention to service coverage, which is strongly relatively more important, especially for car-sharing users, and as important as service characteristics (C2) for non-users. Non-users tend to attach less importance to trip characteristics (C1) over the other two criteria, which, on the contrary, are as important as the service characteristics (C2) for users. It can be seen that there is a cognitive barrier for non-users related to the service itself, which might be due to misconceptions, lack of information, or even past experiences. This prevents non-users from considering whether car-sharing is suitable for the trips they have to make.

At a more detailed level of analysis, the web graph reported in Fig. 2(a) shows that policy-makers especially underscore service availability (C3.1) and give more importance to departure time (C1.3) and trip purpose (C1.4) compared to other groups. Operators focus more on safety (C2.3), service quality (C2.4), and user-friendliness (C2.6). Interestingly, environmental issues (C2.5) and comfort (C2.2) are seen as relatively less important by all groups to attract demand, a striking result in light of the "mainstream debate" on car-sharing services. This result is also better shown in Fig. 3, where C2.5 is the least important car-sharing characteristic for operators to attract demand and the second to last for the non-users group when considering credal rankings. Also, from Fig. 3, in the category car-sharing characteristics (C2), operators attach relatively minor importance to costs (C2.1) compared to the other sub-criteria, which, on the other hand, is the most important characteristic for the other three groups. Such a result is interesting but related to sub-criteria rankings. It does not necessarily point to a different view among stakeholders on the importance of costs, as apparent in Fig. 2(a), where the weight of C2.1 for operators, users, and non-users is very similar. Weights and credal ranking plots give complementary information that should not be mixed. Conversely, user-friendliness (C2.6) seems overrated by operators, even compared to non-users. On the other hand, concerning the sub-criteria related to trip characteristics (C1), there is a clear distinction between the perceptions of operators and policy-makers on one side and users and non-users on the other. The former two groups deem trip purpose (C1.4) as the most influential factor in shaping demand, and the latter two points to travel time (C1.1).

4.2. Bike-sharing stakeholders' views and criteria rankings

Concerning bike-sharing services, Fig. 1(b) shows that trip characteristics (C1) become prevalent for policy-makers, while the other three groups attach the largest importance to accessibility and availability (C3). This indicates the need for policy-makers to refocus when dealing with bike-sharing services. Concerning sub-criteria, Fig. 2 shows that policy-makers are giving more importance to travel time (C1.1) and distance (C1.2), and also non-users compared to users, who get accustomed to using bikes for relatively long trips. Operators, on the other hand, under-evaluate the importance of these two sub-factors and over-evaluate, especially the service availability around the main attraction hubs (C3.1), even compared to C3.2, as noted above. For the other three stakeholder groups, C3.2 is the most important among the twelve considered sub-criteria, as also considered in some literature (Wang and Lindsey, 2019).

By looking at Fig. 4, it can be seen that policy-makers are also critically dismissing environmental concerns (C2.5), whose importance is, on the other hand, primarily overestimated by bike-sharing operators. Regarding this latter point, their difference with car-sharing operators is striking, and it attests to the different cultural backgrounds of the two businesses. Considering rankings among sub-criteria C2 in Fig. 4, it becomes apparent that the most relevant difference in the criteria importance ranking of bike-sharing operators compared to the other stakeholders is the radical underestimation of the relative importance of service costs (C2.1) compared to other sub-criteria falling in the same category. Cost is, in fact, the most important sub-criterion for policy-makers and just below safety (C2.3) for non-users, while C2.1 and C2.3 are of comparable importance for users. On the other hand, Fig. 2(b) shows that the importance of attached to costs per se, i.e., not considered such rankings, is similar for all groups.

4.3. Scooter-sharing stakeholders' views and criteria rankings

Scooter-sharing and bike-sharing services are often jointly considered in transport policy actions and public debate under the more generic "micromobility services" label. Nevertheless, by comparing related plots, it can be easily seen that stakeholders' perceptions are quite diverging. Concerning scooter-sharing, service characteristics (C2) gain a prominent role for both users and policy-makers (see Fig. 1(c)). On the other hand, policy-makers are underestimating the relevance of trip-related characteristics (C1) that are instead deemed important by the other groups when deciding to use car-sharing services. Again, some misalignment in policy-makers views is apparent from those results.

More in detail, safety concern (C2.3) is among the top-rated sub-criteria (see Fig. 2(c)) along with vehicle availability and accessibility (C3.2), and it is the most important one for all stakeholder groups within the C2 main-criterion. This result is not surprising since the introduction of the e-scooter-sharing service has created a new risk of injury (Beck et al., 2020), and its relevance is well-attested in the literature (Ma et al., 2021). Notably, non-users pay less attention to this sub-criterion compared to other stakeholders. Turning our attention to the other shared vehicle characteristics, it can be seen that environmental friendliness (C2.5) receives a higher rank by operators compared to the other groups (Fig. 5). Service users understandably less prioritize user-friendliness (C2.6). However, it is interesting to see that for non-users, it is still relatively less important than service quality (C2.4), unlike the views of both policy-makers and operators.

Finally, it should be noted that, as Fig. 2(c) reveals, unlike the other stakeholders who perceive service availability (C3.1) as one of the most important sub-criterion, operators consider it one of the least important sub-criteria. This indicates the need for operators to focus more on improving their service under this viewpoint, e.g., through more effective fleet relocation policies.

4.4. Overview of the perception gaps

In the following part, the perception gaps that both policy-makers and operators showed compared to users and non-users are analyzed since these are the most important issues to address. Starting from the weights displayed in Figs. 1 and 2, for any given criterion and sub-criterion in all three services, the relative difference *RD* (in percentages) between weights of either policy-makers

Table 7
Suggestions for policy–makers/operators associated with each shared mobility service to adjust their attention to the importance of main/sub-criteria to attract users/non–users.

Main–criteria and sub–criteria	Car–sharing		Bike–sharing		Scooter–sharing	
	Policy–makers	Operators	Policy–makers	Operators	Policy–makers	Operators
C1. Trip–related characteristics	(. / –)	(++ / ++)	(– / –)	(++ / ++)	(+ / ++)	(– / .)
C1.1. Travel time	(. / –)	(++ / ++)	(– – / –)	(++ / ++)	(++ / ++)	(+ / ++)
C1.2. Travel distance	(. / .)	(++ / ++)	(– / –)	(+ / ++)	(++ / ++)	(– – / –)
C1.3. Departure time	(– / –)	(++ / ++)	(– / .)	(++ / ++)	(+ / ++)	(. / +)
C1.4. Trip purpose	(– / – –)	(+ / .)	(– / +)	(++ / ++)	(+ / +)	(– / .)
C2. Shared vehicle characteristics	(. / .)	(– / –)	(+ / +)	(– / –)	(. / –)	(+ / .)
C2.1. Travel cost	(– / –)	(. / .)	(. / .)	(. / .)	(– / – –)	(+ / .)
C2.2. Travel comfort	(– / .)	(. / .)	(++ / +)	(. / –)	(. / –)	(++ / .)
C2.3. Safety	(. / .)	(– / –)	(+ / +)	(– / –)	(– / –)	(+ / .)
C2.4. Service quality	(. / +)	(– / –)	(+ / .)	(. / –)	(. / –)	(+ / .)
C2.5. Environment–friendly system	(. / .)	(. / +)	(++ / +)	(– / – –)	(– / –)	(. / .)
C2.6. User–friendly	(– / .)	(– – / –)	(+ / .)	(– / –)	(– / – –)	(. / .)
C3. Availability and accessibility	(+ / +)	(. / .)	(. / .)	(. / .)	(. / +)	(– / .)
C3.1. Service availability	(++ / ++)	(. / .)	(+ / +)	(– / –)	(– / .)	(++ / ++)
C3.2. Vehicle availability and accessibility	(. / .)	(. / .)	(. / .)	(+ / +)	(+ / +)	(– / –)

and operators and corresponding weights of either users and non-users are computed. Four different relative differences are thus computed. Negative differences ($RD < 0$) indicate that the policy-makers or operators are underestimating the importance of the criterion compared to the users or non-users; therefore, the stakeholder under consideration should pay more attention to that criterion if s/he is willing to fill the gap with the actual or potential service user. Vice-versa, an overestimation of the importance given to the criterion is detected when $RD > 0$.

In our dataset, RD values range from −84 % to +179 %. To help the reader focus on the most significant gaps, all differences are classified according to the following 5-point scale:

- If $RD \leq -50$ %, thus indicating that the weight given by the policy-makers or operators is not more than half of the weight given by users or non-users, a "++" is used, meaning that the stakeholder (policy-makers or operators) should pay **much more** attention to the criterion.
- If -50 % $< RD \leq -20$ %, then a "+" is used, meaning the stakeholder should pay **more** attention to the criterion.
- If -20 % $< RD < +25$ %, the perception gap is considered not too wide, and a "." is used. There is no compelling need to adjust stakeholders' views in this case.
- If $+25$ % $\leq RD < +100$ %, then a "–" is used, meaning that the stakeholder should pay **less** attention to the criterion.
- If $RD \geq +100$ %, then the stakeholder should pay **much less** attention to the criterion since the weight given by her is at least twice the weight given by users or non–users; therefore, a "– –" is used.

The results of this rating exercise are reported in Table 7. In each cell, the left rating refers to the stakeholder mentioned in the column heading compared to the service user, and the right rating refers to the service non–user.

Concerning car-sharing, as already mentioned, policy-makers should focus their attention on service availability to align with both users' and non-users' views, whereas trip purpose is not so strongly related to specific trip purposes (and also, to a lesser extent, to other trip related characteristics) as they believe. By comparing columns 2, 4, and 6 of Table 7 in more general terms, it seems that policy-makers have larger problems in understanding the users' and non-users' views of bike-sharing, especially of scooter-sharing users and non-users, compared to car-sharing. This could be due to the fact that the latter services (except station-based bike-sharing) have been introduced in Turin only in recent years. More specifically, policy-makers overestimate the importance of travel time, especially for users, as already mentioned, and should, conversely, pay more attention to both travel comfort and environmental sustainability issues to be in the users' shoes. Conversely, they severely underestimate the importance of trip-related characteristics for scooter-sharing. Finally, they should think that both travel costs and user-friendliness are not so relevant to attracting non-users.

Both car-sharing and bike-sharing operators should consider that trip characteristics impact users' and non-users' decisions larger than they believe. Also, they should play down the importance of user-friendliness for car-sharing customers and environmental-friendliness for those not using bike-sharing. Quite interestingly, policy-makers and operators' views on such sustainability issues related to bike-sharing are at odds, with the position of both users and not users somewhat in between. Finally, scooter-sharing operators' views seem more in line, especially with non-users. This is good news when designing campaigns to enlarge their customer base, even if they should not disregard travel time issues and especially service availability. To strengthen the fidelity of their customers beyond service availability, it is critical to consider more comfort issues.

5. Discussion and conclusions

This study aimed to identify the gap between the perceptions of different stakeholders in the car–sharing, bike–sharing, and scooter–sharing services regarding the factors affecting demand. Analyses were carried out using the Bayesian BWM, a state–of–the–art method used in multi-criteria analyses. To do this, three main–criteria and twelve sub-criteria are compared. Four stakeholders (policy–makers, operators, users, and non–users) made this comparison. This helps to understand their views on the importance of each sub-criterion that people can consider in their decisions to use the car–sharing, bike–sharing, and scooter–sharing services (each shared mobility service is studied separately).

Adopting this approach brings several advantages: it provides a comprehensive understanding of stakeholder priorities, ensures robust and consistent comparisons across diverse groups, and highlights significant perception gaps. Without this approach, key insights into stakeholder misalignments would be missed, potentially leading to suboptimal policy and service adjustments that fail to effectively meet user and non-user expectations. The application of the Bayesian BWM method enhances the reliability of the results by offering a more structured and less data-intensive way to perform pairwise comparisons, ensuring that decision-making outcomes are consistent and reflect the actual priorities of different stakeholder groups.

Comparing the findings with prior studies reveals that our results align with some but diverge from others. For instance, previous research has highlighted the importance of service availability and accessibility in car-sharing (Juschten et al., 2017), consistent with our finding that availability and accessibility are critical for car-sharing users and non-users. However, unlike studies that emphasized environmental concerns (Schulte and Voß, 2015) and travel comfort (Schaefers, 2013) as important factors affecting car-sharing demand, our results show that environmental issues and comfort are seen as relatively less important by all groups to attract demand. This suggests that while environmental friendliness and travel comfort are essential considerations, they may not be the primary drivers for users who prioritize practical aspects like vehicle availability and accessibility. Hence, for car-sharing services to be effective, there needs to be a balance between sustainability initiatives and practical service enhancements, ensuring that operational efficiency and user accessibility are prioritized to improve commuter experiences and satisfaction.

This experimental design contributes original insights to the field of multi-criteria analyses and Bayesian BWM applications. Unlike past studies that only addressed the importance of some of these twelve sub-criteria, this study ranks and compares all of them to determine their relative importance from each stakeholder's perspective. In particular, more qualitative criteria, including service quality and safety, environment–friendly systems, and user–friendly have been underexplored in previous research. Furthermore, while most studies have focused solely on user perspectives (Axsen and Sovacool, 2019; Sarker et al., 2024) or used semi-quantitative, focusing on supply, planning, and policy aspects rather than traveler perceptions (Nikitas et al., 2024), this study considers four distinct stakeholder groups, providing more comprehensive analysis. By analyzing and comparing the similarities and differences (gaps) in the stakeholders' perspectives of each shared mobility service, the study offers actionable suggestions for policy–makers, and operators to adjust their views to attract non–users and better satisfy users. Therefore, perceptual gaps between policy-makers and operators on one side and users and not users on the other are particularly interesting. Policy-makers are generally more aligned with the views of both users and non-users of car-sharing compared to other services, even if they underestimate the importance of car-sharing availability. They overestimate the importance of trip characteristics for bike-sharing, which is more critical for scooter-sharing. Travel costs and user-friendliness are much less relevant than they think to scooter-sharing non-users, while travel comfort and environmental friendliness should be more considered to fit the bike-sharing users' viewpoint. Service providers, both car-sharing and bike-sharing operators, should focus less on actual trip characteristics and more on user-friendliness to satisfy car-sharing users better and on more sustainability issues to attract non-users to bike-sharing. Scooter-sharing operators better align with non-users' views, even if they should consider more travel time and service availability, whereas they are not paying enough attention to comfort compared to their customers.

Recognizing these perception gaps is fundamental to boosting demand for shared mobility services. Policy-makers and operators must first understand the difference between their perceptions of users' and non-users' expectations and the actual expectations and behaviors. After identifying this, they can tailor their services to align with the genuine importance of various factors, prioritizing those significantly influencing user and non-user choices that can be feasibly modified. It is therefore important to underline that, unlike in other MCDM studies where the final goal is to reach a synthesis among different viewpoints, all being legitimate, here the perception gaps should be addressed by operators and policy-makers by "simply" changing their views to conform as much as possible to those of users and non-users of shared services.

A complementary strategy involves marketing campaigns to align user and non-user views with the needs and views of operators and policy-makers. Policy measures and environmental conditions also play crucial roles in shaping perceptions and behaviors. Push measures (e.g., restrictions on private vehicle usage) and pull measures (e.g., subsidies for shared mobility) can nudge users toward these services. External factors like traffic conditions and parking availability significantly impact individuals' decisions to opt for shared mobility, necessitating their inclusion in comprehensive strategies to boost adoption.

The detailed implementation and operational steps we recommend are reported in Fig. 6 for car-sharing, Fig. 7 for bike-sharing, and Fig. 8 for scooter-sharing mobility services. By implementing these guidelines, operators, and policy-makers can better align their services with user needs and preferences and ultimately increase the acceptance and satisfaction of shared transportation services.

Considering the limitations of this study and recommendations for future research, it can be mentioned that the consistency checks through the above–mentioned input–based approach could be made in real-time during the interview. In case of any issue,

1. Increase service availability and accessibility
    - Policy-makers
        - Implement policies to expand car-sharing coverage areas, ensuring vehicles are available in underserved locations.
        - Introduce incentives for operators to deploy more vehicles in high-demand areas.
    - Operators
        - Use data analytics to identify high-demand locations and strategically place vehicles to ensure maximum availability and accessibility.
        - Implement dynamic fleet management to relocate vehicles based on real-time demand.
2. Enhance focus on trip-related characteristics
    - Operators
        - Develop features that cater to trip-related needs, such as flexible booking options, real-time tracking, and detailed trip analytics.
3. Reduce user costs
    - Operators
        - Introduce tiered pricing models with discounts for frequent users or off-peak usage.
        - Offer promotional rates for first-time users and implement a referral program to attract new customers.
        - Consider partnerships with local businesses for discounts and deals.
        - Emphasize free-floating car-sharing options to increase flexibility and convenience for users.

Fig. 6. Guidelines for car-sharing operators and policy-makers to align their views with those of users and non-users.

1. Improve vehicle availability and accessibility
    - Policy-makers
        - Provide grants or subsidies to bike-sharing operators to expand their fleet.
        - Improve infrastructure, such as bike lanes and docking stations, to enhance accessibility.
    - Operators
        - Transition to a free-floating bike-sharing model to increase flexibility and reduce the need for users to return bikes to specific stations.
        - Implement geo-fencing technology to ensure bikes are available in high-demand areas.
2. Emphasize trip-related characteristics
    - Operators
        - Introduce features that enhance the biking experience, such as integrated navigation systems, trip planning tools, and real-time traffic updates.
3. Address underestimated and overestimated aspects by government members
    - Policy-makers
        - Recognize and address the underestimation of bike-sharing characteristics, availability, and accessibility by promoting policies highlighting these factors.
        - Adjust focus from overestimated trip-related characteristics to reflect user and non-user priorities more accurately.
4. Prioritize safety and service quality
    - Policy-makers
        - Implement safety standards and regulations to ensure a secure biking environment.
        - Educate the public about safety protocols and benefits of bike-sharing.
    - Operators
        - Enhance safety measures and ensure regular maintenance checks.
        - Improve service quality by providing well-maintained bikes and ensuring the reliability of bike-sharing services.

Fig. 7. Guidelines for bike-sharing operators and policy-makers to align their views with those of users and non-users.

1. Enhance service quality and comfort:
    - Policy-makers
        - Set and enforce high safety and quality standards for scooter-sharing operators to ensure user confidence in the service.
    - Operators
        - Invest in high-quality scooters with improved safety features and comfort enhancements.
        - Regularly maintain and upgrade the fleet to ensure a smooth and reliable user experience.
        - To increase demand, focus on providing more comfort services and high-quality scooters in high-demand locations.
2. Increase service availability
    - Policy-makers
        - Create designated parking zones and charging stations for scooters in key locations to improve availability and accessibility.
    - Operators
        - Use predictive analytics to deploy scooters in high-demand areas during peak times.
        - Implement a real-time dynamic rebalancing strategy to move scooters from low-demand to high-demand areas.
3. Focus on travel costs
    - Policy-makers
        - Provide subsidies or tax incentives for scooter-sharing operators to lower user costs and make the service more affordable.
    - Operators
        - Offer competitive pricing models, such as pay-per-minute or subscription plans with discounts for frequent users.
        - Introduce loyalty programs and seasonal promotions to attract and retain users.
4. Improve trip-related characteristics
    - Policy-makers
        - Ensure policies and infrastructure support efficient trip planning and execution, such as clear signage and dedicated scooter lanes.
    - Operators
        - Introduce features that enhance the trip experience, such as real-time tracking, planning tools, and flexible booking options.

Fig. 8. Guidelines for scooter-sharing operators and policy-makers to align their views with those of users and non-users.

the interviewee could then have the opportunity to correct their judgments on the fly, either through a face–to–face survey protocol or through a web-based survey that only accepts those responses for which the consistency levels are less than the thresholds. This can lead to better survey efficiency and fewer observations that need to be excluded.

Declaration of competing interest

None.

CRediT authorship contribution statement

Ehsan Amirnazmiafshar: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Methodology, Formal analysis, Data curation, Conceptualization. **Marco Diana:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Methodology, Formal analysis, Data curation, Conceptualization.

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