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Comparative mode choice analysis of university staff commuting travel preferences

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Surveying citizen preferences on transportation modes when commuting is a major issue in urban transport planning. Most of the current methods approach the problem through the attributes of choices thus forecasting the demand indirectly. This paper aims to analyze a survey of commuting students and university staff by two direct preference models: the Analytic Hierarchy Process and the Best-Worst Method. Both techniques are based on pairwise comparisons; consequently, the commuting transport alternatives can be directly compared with each other, and the results are comparable, too. However, the two methods differ in the number and the nature of comparisons and in the consistency check, thus they can be regarded as competitors. A real-world case study on commuting student groups provides a better understanding of the proposed methodology. As a result, it can be stated that despite their low utilization in the transportation field, both the Analytic Hierarchy Process and the Best-Worst Method are applicable to mode choice preference surveys, and they produce comprehensive final outcomes. Therefore, the well-known tools of mode choice can be extended by Multi-Criteria-Decision-Making techniques to increase the efficiency of transport demand prediction. The extension is beneficial to avoid the bias of other methods in converting attribute evaluations to real mode choice decision, as both models, especially the Best-Worst approach, requires less cost and time than the mainstream techniques.

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1. Introduction

Analyzing commuting travel patterns plays a significant role in urban planning and development. Commuter trips cover the majority of all trips in the urban transportation system (Lo et al., 2016), and the mode choice in this type of travels has a severe impact on the system's operation. In scientific literature, two basic approaches exist to analyze mode choice.

On the one hand, visualization techniques collect enormous amount of data (by applying e.g., Geographic Information Systems or sensors on the vehicles) on the movements of citizens then process and analyze the collected information (Wallner et al., 2018). Although an evident merit of this approach is a complete database on the actually conducted trips and number of passengers, the motivation of transport users or non-users remains uncovered.

On the other hand, a large group of techniques strive to reveal the motivation to use a mode and the attitude toward various travel modes by preference analysis. A possible approach in this case is to determine the preference of citizens by finding the factors influencing the decision and by examining the nature and relation of these attributes. Structural Equation Modelling (SEM) is a widely applied methodology in this domain. This modeling technique aims to determine endogenous and exogenous latent variables in travel preferences and draws conclusions by examining the correlations among the observed variables and the latent ones (Stuart et al., 2000, Eboli and Mazzulla, 2012, Jiang et al., 2017, Najaf et al., 2018).

Furthermore, factor and cluster analysis are tools for revealing the characteristics of mode choice determinants (Vicente and Reis, 2016). The benefit of these models is their capability of highlighting the most important service quality elements from the aspect of passengers; thus, the operator of the system can be informed on the crucial factors to be developed. However, this approach is not flexible in terms of defining the attributes. In the passenger survey, the respondents cannot add other attributes of the service quality, even if they think those are more important than the provided factors. Consequently, the real intention of the passengers for mode choice can be mostly indirectly forecasted.

Other models exist to analyze passengers' perceptions and mode choice directly not via decision attributes. Exploring citizens' image on transportation and customers' feelings is a possible solution for direct determination. The mode choice associated with citizens' feelings is studied by Shiftan et al. (2015) in a case study, which targets to reveal passengers' loyalty to various modes of transportation. Van Lierop and El-Geneidy (2018) apply combined binary logit models to reveal how public transport (PT) image influences directly the mode choice of citizens.

The current paper aims to evaluate the applicability and added value of MCDM based methods for mode choice analysis. Instead of reaching the selection of mobility types by the commuters through their perception or satisfaction with some specific attributes of transport service quality, the aim is to derive their attitudes by applying some stated comparisons of transportation modes. This objective requires the application of special methods. Thus, two widely applied Multi-Criteria Decision-Making (MCDM) techniques: the Analytic Hierarchy Process (AHP) and the Best-Worst Method (BWM) are selected. The reason for selecting both is to validate the BWM for mode choice analysis. Compared to the AHP, the BWM has significant practical advantages in passenger surveys. In case of the BWM, less time and effort are needed to complete the questionnaire, the responses are generally more consistent, and the response rate is much higher than in an AHP survey (Rezaei, 2016).

It has to be stressed that there are newly emerged methods aiming the reduction of pairwise comparisons even more, e.g. the Full Consistency Method (FUCOM) created by Pamucar et al (2018). FUCOM requires less pairwise comparisons (*n-1*) than BWM, and produces higher consistency based on the results of existing numerical examples and case studies (Stevic and Brkovic, 2020). However, it has to be emphasized that reducing the number of comparisons does not only mean unburdening the decision makers, but also losing some information on the perceived relation of each missing pairs of alternatives or criteria. Thus, the applied MCDM model should balance between the affordable number of required comparisons and the loss of information on the (intermediate) pair relations of the alternatives. In our specific case, the direct relations of the certain modes are very important, thus the reduction of comparisons would cause loss of important information. Therefore, in our study we decided to apply only AHP and BWM to preserve the gained information on pair relations of the transport modes.

Even though the AHP is very popular in supporting transportation decisions, for mode choice analysis, it is rarely applied. In current study, an attempt is made to fill the scientific gap triggered by ignoring the MCDM methods in mode choice analysis by introducing two models and a real-world case study, in which both methods are utilized. Note that even if both techniques are based on pairwise comparing attributes and alternatives, their approach is different in the nature of comparisons: AHP considers all possible pairs, while BWM anchors the best and the worst attributes (or alternatives), where one member of the pair is always either the best or the worst attribute. Moreover, the consistency check is also different in the case of the two methodologies. Consequently, the research question arises, whether applying both techniques to the same decision problem and to the same evaluator pattern could reveal their compatibility and might verify the application of both methods to the examined problem. In this case the current set of mode choice analysis methods can be extended by less time and cost consuming techniques, which might facilitate the application of preference surveys to support transport policy related decisions.

The rest of this paper is organized as follows. A literature review summarizes the most important references on commuting mode choice. In the methodology section both the AHP and the BWM are presented. The results section introduces passenger surveys conducted by the AHP and the BWM. After the analysis, a separate discussion section is included. Finally, conclusions related to the application of the two methodologies are drawn, and practical suggestions are provided for conducting passenger surveys, as well.

2. Literature review

Travel mode choice is a complex process, where several factors, such as social background, psychological status, habitual behavior, and personal attitudes, play a role. Transportation mode choice is influenced by such parameters as the individual features of a traveler, the characteristics related to the trip and to the transportation network (Ortuzar and Willumsen, 2011). Another classification by Yang et al. (2018) includes the following five groups: travel demand parameters, transportation modes, socio-demographic information, subjective attitudes, and perceptions.

Sustainable travel behavior triggers the choice of specific transportation modes, such as PT, walking, and cycling. These modes are considered sustainable in terms of emissions and health effects (Lind et al., 2015). According to Anagnostopoulou et al. (2018), with efficient measures, behavioral change can be achieved. In the scholars' approach, the aim is to nudge users on a personalized level to make more sustainable choices. Personalized interventions and persuasive technologies are used to reach behavioral change. Schneider (2013) uses a new approach to increase sustainability by providing attractive solutions to car users to choose rather walking and cycling as a transportation mode. The researcher identifies both soft and hard measures to promote walking and cycling, i.e., awareness, safety, convenience, cost, and information about sustainable transportation.

Different methods can be used to analyze user preferences related to transportation modes. Discrete choice models are widely applied to determine factors affecting transportation mode choice. These models can predict individual decisions and can be used as effective tools in policy planning (Muro-Rodrígez et al, 2017). In case of these models, travel behavior is analyzed in a way where the traveler has to choose between different alternatives regarding transportation modes (Le Pira et al, 2017).

Hilgert et al. (2016) analyze how commuting mode choice patterns are affected by individual characteristics and which factors influence this variation. The results indicate that transportation mode choice is determined by socio-demographics, tour characteristics, the availability of car and PT pass. Miletic et al. (2017) try to find out to what extent demographic and socioeconomic characteristics affect the usage of car and PT. The researchers use binary logistic regression analysis. The results show that preference is primarily influenced by the age, the size of the settlement, the accessibility of PT, and the number of vehicles in the household. Kotoula et al. (2021) conduct research among students on travel behavior with an aim to examine various aspects influencing mode choice, such as travel distance, travel time, comfort, and safety. The result demonstrates that distance and time are the most important factors. In the research of Ko et al. (2019), it is investigated how influential factors are associated with transportation mode choice decisions. As a result, it becomes clear that income, occupation, gender, and residence duration tend to influence mode choice significantly.

Specifically, found by Owen and Levinson (2015), in case of commuting mode choice, a fundamental aspect of the model is that travelers consider cost minimization as the key driver of their choices. Almasri and Alraee (2013) develop a mode choice model for work trips. The results show that the factors significantly affecting the choice of transportation modes are total travel time, total cost, ownership, distance, and age. The developed model is able to predict travel choices, but it does not evaluate and suggest transportation modes.

Ye and Titheridge (2017) examine the role of the built environment and the attitudes in commute satisfaction when choosing the best transportation mode. The researchers use Structural Equation Modeling (SEM), and it is demonstrated that the built environment has solely indirect effects through influencing commuting characteristics. Furthermore, it is found that active mode users have the highest level of commute satisfaction. Balaji et al. (2019) use the AHP to prioritize routes and improve customers' satisfaction. The scholars find that cost and delay are relevant factors when choosing routes and modes. Echaniz et al. (2019) model users' satisfaction considering missing information. The researchers try to reduce the amount of information collected without compromising the results. Predictive models are used to fill the gap of missing information. It is observed that around half of the data is enough to estimate the answers of the original survey with small variations.

In the research of Choudhury et al. (2018), the acceptability of emerging smart mobility options (e.g., shared taxi, park and ride, school bus) is investigated with a comprehensive stated preferences survey. It is found that for commuting trips, the improved versions of PT modes are favored over smart mobility options. Another study by Abasahl et al. (2018) investigates the differences in the bicycle mode choice of specific user groups. Participants with good cycling skills are less likely to choose car as a transportation mode. However, travel time concern may shift mode choice toward non-active transportation options. Additionally, the access to PT and car strongly shifts users to choose non-active modes over the active ones.

Ton et al. (2019) elaborate a mode choice model including a set of transportation modes (i.e., walking, cycling, PT, and car). Based on panel data in combination with an additional survey focusing on active modes, the study estimates which parameters (i.e., individual, household, weather, trip characteristics, and built environment) influence mode choice. The results show that active modes are the most sensitive to the changes in the trip characteristics and the built environment. Another study by Ding and Zhang (2016) aims to estimate travel behavior by dividing travelers into groups based on their personal characteristics. The grouping is achieved by cluster analysis, and two transportation modes are investigated (i.e., PT and car). The travel information is collected by using both a revealed preference and a stated preference survey. The mode choices are estimated by using a discrete choice model, and they are compared with the original choices. It is found that the accuracy of the mode choice estimation by using individual grouping is higher than considering the whole group together.

In the work of Cheng et al. (2019), a Random Forest method is used to analyze and predict travel mode choices with higher accuracy and less computation time. It is found that the built environment generally contributes more compared to the household and individual attributes. In addition, the mode choice behavior of commuters is assessed by Ravi Sekhar et al. (2016) by using Random Forest Decision Tree method. From the results, it can be seen that the developed method provides high prediction accuracy. In a recent paper, Zhao et al. (2020) conduct a comprehensive comparison of machine learning and logit models. The evaluation is performed by using a stated-preference survey. It is found that the random forest model has higher predictive accuracy compared to the multinomial logit model and the mixed logit model. However, the random forest model produces behaviorally unreasonable effects.

Another recent method to support mode choice estimation is the BWM, where the suitable weights for the criteria are defined and the ranking of alternatives are created by the combination of other methods, such as the rough Simple Additive Weighting (SAW), the Analytic Hierarchy Process (AHP), or Rough Strength Relation (RSR) method. The application domains cover logistics processes (Stevic et al., 2017), automotive manufacturing (Fartaj et al., 2020), and PT quality (Moslem et al., 2020). For example, AHP is used to determine the location of emergency medical services. In the work of Alosta et al. (2021), several criteria are compared, and a ranking of different alternatives is realized. BWM is used to select providers in logistics applications, where several scenarios are created, the proposed model is compared with other models, and Spearman's correlation coefficient confirms the applicability of the proposed approach (Muravev and Mijic, 2020). Another application of BWM is realized by Fazlollahtabar and Kazemitash (2021) to select the most sustainable supplier, where several criteria and subcriteria are used to reach an optimum. Finally, TOPSIS method is used by Pamucar and Dimitrijević (2021) to find the most suitable units for procurement purposes, where four alternatives are listed. Based on the provided examples, the proposed methods seem to be very useful tools for decision making.

In order to evaluate mode choice, usually utilities are assigned to each transportation mode, and the mode with the highest utility is chosen. To provide a suitable utility function, first, the parameters need to be defined. According to De Vos et al. (2016), the utility theories focus on the weight of those attributes which support mode choice decision. In addition, the parameters of a suitable utility function need to be defined (Sun et al, 2018). In most cases, modern informatics-based solutions are proposed as means for changing travel behavior (Nybom, 2014). The results show that decision-making includes the planning process, and to support this, sufficient travel information should be available. However, mode choice depends on feelings and emotions, which is closely related to satisfaction and subjective well-being. A research by Idris et al. (2015) shows that travelers have positive emotions toward their chosen transportation mode thus influencing the personal parameters of the mode choice, which has to be explored. Bouscasse et al. (2018) analyze how mode choice habits are dependent on situational and socio-psychological factors. The scholars create a theoretical model in which the effect of environmental concern on mode choice is investigated and modified by the indirect utility of traveling. The results show that those people who have a high environmental concern perceive traveling with PT easier, at the same time, low environmental concern generates motives for car use. Thus, perceptions alone may increase PT usage and reduce car usage.

The significance of students' mode choice judgment has been evaluated in several studies. Guzman and Diaz (2005) evaluate students' transport related choices of Ateneo De Manila University and Miriam College in Philippines. The outcome of the analysis highlights that travel cost and travel time are key determinants of the students' choices. Similarly, in USA at Texas A&M University, Maneesh., et al. (2007) also illustrate that the most significant factors of students' transport mode choice are travel cost and travel time. Whalen (2011) improves a multinomial logit model to evaluate students' transport mode choice in McMaster University in Hamilton, Canada. The findings show the travel time is the most important indicator. Volosin (2014) evaluates students' transport mode choice in Arizona State University, USA, where the multinomial logit model is applied. Based on the results it can be seen that the students' travel patterns vary substantially from the rest of the population. Nguyen-Phuoc et al., (2018) use a developed conditional logit regression model for evaluating transport mode choice of university students in Danang, Vietnam. They find that except for travel time, the gender characteristics is among the main factors influencing student's mode choice.

Based on the conducted literature review we can state that the dominating models for examining transport mode choice are based on Discrete Choice Modelling (DCM) and Structural Equations Modelling (SEM). These models are mathematically well-proven and statistically representative. However, there are two main limitations that can be overcome by our proposed approach. On the one hand, both DCM and SEM based surveys offer a limited scale in the evaluation process for the participants. Most frequently, the 5-grade Lickert-scale is applied that provides a restricted assortment of values to express feelings towards the criteria of the examined problem (Kandasamy et al, 2020). As highlighted, there is a gap in the existing body of knowledge on mode choice analysis, i.e., utilizing such methods that contain an immanent consistency check (both AHP and BWM are capable of checking the consistency of the evaluations), thus providing more trustworthy outcomes than other methods. Also, the presented methods apply extended scales compared to the mainstream discrete choice models. Instead of the well-known 5-grade Lickert scale, AHP and BWM applies a 17-grade scale to express inferiority or superiority among the criteria, which enables a more sophisticated evaluation, and supports the expression of smaller differences in preferences. On the other hand, the reliability of participants' scoring is not checked directly in the DCM and the SEM models. The consistency of evaluations might be crucial, especially, when the general public is involved in a survey. In case of AHP and BWM, the consistency of scoring is checked before the calculation of the results, thus the inconsistent evaluations (that fail to complete the consistency threshold) are filtered, so they cannot bias the final outcomes of the calculation. Since our objective is to examine the mode choice preferences of commuting university staff, the requirement of a sophisticated scale and consistency check should be fulfilled simultaneously. Therefore, the proposed AHP and BWM methods seem more promising and more suitable than the mainstream techniques applied.

3. Methodology

3.1 The AHP approach

The AHP approach is one of the most conducted and practical approach to group an unstructured complex assumption into several components in a hierarchical structure while giving subjective values about the relative importance of each variable and determining which variable has the most significant priority to provide the final outcomes of the scenario. The decision-making approach purely assigns the most important alternative or criterion. The focal point in the AHP approach is to have a purposeful hierarchy with the basic evaluation of evaluator belief (Saaty, 1977). Figure 1 defines the main steps of conducting the AHP approach for deriving weights. An example of the calculation process for the AHP method is presented in Appendix A.

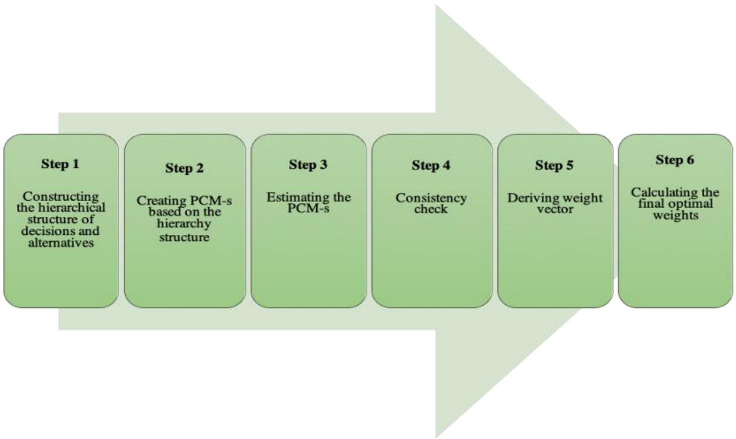

Figure 1. The main steps of the AHP approach to obtain the weights of the criteria or alternatives

The following steps are required to conduct the AHP method:

Step 1. Constructing the structure of the problem and defining the related criteria and alternatives

Step 2. Creating the hierarchy of the structure by setting up a pairwise comparison matrix (PCM)

Step 3. Estimating the PCM and establishing priority by evaluating the PCM on a scale (Table 1)

Table 1. Judgment scale of relative importance for pairwise comparison (Saaty, 1977)

Numerical values	Verbal scale	Explanation
1	Equal importance of both elements	Two elements contribute equally
3	Moderate importance of one element over another	Experience and judgment favor one element over another
5	Strong importance of one element over another	An element is strongly favored
7	Very strong importance of one element over another	An element is very strongly dominant
9	Extreme importance of one element over another	An element is favored by at least an order of magnitude
2,4,6,8	Intermediate values	Used for compromise between two judgments

Step 4. Checking the consistency of the answers

The consistency of the matrix has to be examined by Saaty's Consistency Index (*CI*) and Consistency Ratio *(CR)* < *0.1* because in some cases the experiential matrices are not consistent:

$$CI = \frac{\lambda_{\max} - n}{n-1} \tag{1}$$

where *CI* is the Consistency Index, λ_{max}. is the maximum eigenvalue, and *n* is the number of rows in the matrix. *CR* can be determined by:

$$CR = \frac{CI}{RI} \tag{2}$$

where *RI* is the random Consistency Index.

Saaty (1977) provides the calculated RI values for matrices of different sizes as shown in Table 2.

Table 2. Consistency indices for a randomly generated matrix

n	2	3	4	5	6	7	8	9
RI	0	0.58	0.9	1.12	1.24	1.32	1.41	1.45

Step 5. Calculating the weights by deriving the eigenvectors from the PCMs
The dominant eigenvector of the PCM can be determined by Saaty's eigenvector method. If M is a consistent matrix, then the eigenvector w can be calculated by finding its maximum eigenvalue (λ_{max}). $w = \lambda_{max} M$. Then the eigenvector w can be computed as $(M - \lambda_{max}\, I)\, w = 0$, where $\lambda_{\max}$ is the maximum eigenvalue of the matrix M.

Step 6. Calculating the final weights
For aggregating the individual responses to reach a final group outcome, we utilize the aggregation of individual judgments method, where a global pairwise comparison matrix is constructed by taking the individual M matrices and computing the geometric mean of their values in certain positions of the matrix.

$$f(x_1, x_2, \dots, x_h) = \sqrt[h]{\prod_{k=1}^{h} x_k}\ . \tag{3}$$

where $x_1, x_2, \dots, x_h$ denotes entries in the same position of the h number of M pairwise comparison matrices filled in by the decision-makers in the same group.

3.2 The BWM approach
The BWM approach has been recently created for evaluating complex decisions, where multiple factors or alternatives are involved. The reliability and efficiency of the BWM is quite high with respect to the amount of data needed. Like the AHP approach, the BWM uses pairwise comparisons to compute the weight scores of the factors and alternatives. However, the BWM approach requires fewer comparisons *(2n-3)* compared to the AHP approach *(n*(n-1)/2)* (Rezaei, 2016). Moreover, the BWM is easy to apply and more reliable compared to other methodologies (Rezaei, 2016). The main steps of the BWM approach for deriving weights are depicted in Figure 2. Furthermore, an example of the calculation process for the BWM method is presented in Appendix B.

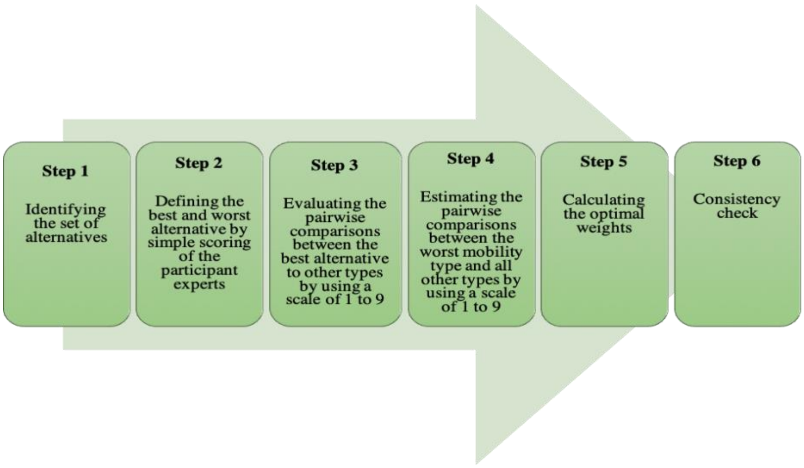

Figure 2. The main steps of the BWM approach to obtain the weights of the criteria or alternatives
To provide an overview of all the stages for current survey, the phases are defined in the following order:

Step 1. Identifying the set of alternatives, in this study, the mobility type alternatives.
In the first step, the decision-maker defines *n* alternatives ($A_1, A_2, \dots , A_n$) that are used to make the judgment.

Step 2. Defining the best and the worst alternatives by the simple scoring of the participant experts.

Step 3. Evaluating the pairwise comparisons between the best alternative and the other types.
The evaluation is conducted by using a scale of 1 to 9, where 1 means "equal importance", and 9 means "extremely more important". The result of this step is represented by the following best-to-others vector:

$$V_B = (v_{B1}, v_{B2}, \dots, v_{Bn}) \tag{4}$$

where v_{Bj} is the preference of the alternative *B* (i.e., the most important or the best) over the alternative *j* and $v_{BB} = 1$ In the model of this study, *n = 6* since six alternatives are compared.

Step 4. Making pairwise comparisons between the worst mobility type and all other types.
A scale of 1 to 9 is used. The result of this step is represented by the following vector:

$$V_j = (v_{1W}, v_{2W}, \dots, v_{nW}) \tag{5}$$

where v_{jD} is the preference of the alternative *j* (i.e., the most important or the best) over the alternative *W* and $v_{WW} = 1$ *n = 6* since six alternatives are compared in the model of this research.

Step 5. Calculating the final optimal weights ($D_1^*, D_2^*, \dots, D_n^*$) of the mobility types and the indicator of the optimal consistency of comparisons ξ^*.
The maximum absolute difference has to be minimized by:

$$\min max_j \left\{ \left| \frac{D_B}{D_j} - v_{Bj} \right|, \left| \frac{D_j}{D_W} - v_{jW} \right| \right\}$$

$$\sum_j^{s.t.} D_j = 1, \; D_j \geq 0, \text{for all } j \tag{6}$$

Afterward, the solution could be obtained by solving the following linear programing:

$$\begin{aligned} &\min \xi^* \\ &\text{s.t.} \\ &\left| \frac{D_B}{D_j} - v_{Bj} \right| \leq \xi^*, \text{ for all j} \\ &\left| \frac{D_j}{D_W} - v_{jW} \right| \leq \xi^*, \text{ for all j} \\ &\sum_j D_j = 1 \\ &D_j \geq 0, \text{for all } j \end{aligned} \tag{7}$$

Step 6. The following formula computes the CR to check the consistency of the comparisons (Rezaei, 2016).

$$\text{Consistency Ratio} = {\xi^*}/{\text{Consistency Index}} \tag{8}$$

where the CI is given in Table 3 and gained by random experiments for different number of comparisons.

Table 3. The CI values for computing the CR (Rezaei, 2016)

v_{BD}	1	2	3	4	5	6	7	8	9
CI	0	0.44	1	1.63	2.3	3	3.73	4.47	5.23

3.3 The Spearman's rank correlation coefficient

For defining the grade of similarity between the results of BWM and AHP, we involve a nonparametric rank statistic method (Spearman, 1904), and compute the Spearman's rank correlation coefficient (R).

Generally, the following is formula used as a mathematical notation for Spearman's rank calculation:

$$R = 1 - \left(\frac{6\sum d^2}{m^3 - m}\right) \tag{9}$$

where d is the difference between ranks and m is the number of the ranked elements.

The result of the formula (9) is always between one and minus one. Plus one refers to perfect positive correlation and minus one refers to a perfect negative correlation, while zero represents the lack of correlation of the compared rankings.

4. Results

The focal point in this research is the construction of a general model for the mode choice problem of commuting. In this study, no criteria are adopted, solely the alternatives (i.e., the transport modes themselves) are estimated since this research relies on expert considerations and do not strive to influence their decisions by any criteria selection. In the applied survey, six mobility types (i.e., PT, Car, Car-pooling, Walking, Bike, and Home office) are utilized as listed in Figure 3.

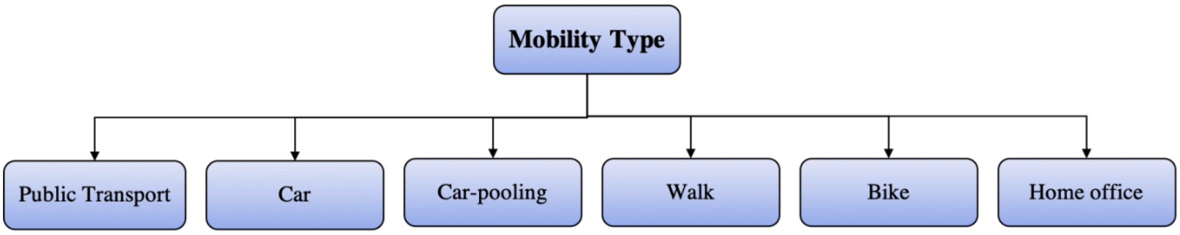

Figure 3. Mobility types

In the real-world case study, in the first quarter of 2020, two passenger surveys were conducted by the AHP and the BWM in a Turkish city, Mersin. We received 56 completed questionnaires from transport experts studying and working at a university dealing with transport studies. It should be noted that including a random pattern of citizens or layman would have required the application of fuzzy or rough sets in the model to deal with uncertainty, however, in our case the selected respondents with professional knowledge made possible to apply the traditional AHP and BWM models. The sample is further divided into three groups based on the commuting distance from home to the campus. In the analysis of mid-distance and long-distance commuters, walking is not considered.

- Group 1. short-distance commuters from 1-10 km, where 26 evaluators participate
- Group 2. mid-distance commuters from 10-40 km, where 21 evaluators participate
- Group 3. long-distance commuters from over 40 km, where 9 evaluators participate

The basic characteristics of the experts can be found in Table 4. The gender ratio is balanced, while the age and educational level are somewhat biased because several young experts, including students, are involved in the study.

Table 4. The basic characteristics of the respondents

Evaluators = 56		%
Gender	Male	44.6
	Female	55.4
Material statue	Married	36.8
	Single	63.2
Age	18-30 years	42.0
	31-50 years	36.4
	> 50 years	21.6
Educational level	Primary school	2.4
	Secondary school	2.6
	High school	26.5
	BSc degree	26.0
	MSc/PhD degree	42.5
Working status	Student	26.2
	Researcher	23.8
	Teacher	34.0
	Retired	16.0

4.1 The findings of the AHP

After selecting the commuting alternatives and implementing the AHP logic, the following short questionnaire is created.

- "How long do you commute to work from your home?"
- "Please compare mobility type alternatives related to your travel by using a scale of 1 to 9!"

The following steps are required to conduct the AHP method:

Step 1. The problem is defined, where transport mode choice is to be estimated.
In our case, alternatives related to commuting are selected by experts in the related field considering the distance for each group (for Group 1 there are 6 alternatives, for Group 2 and 3 there are 5 alternatives).

Step 2. The hierarchy structure is conducted.
The hierarchy structure in our case is constructed of the alternatives (Figure 3), which are defined by experts in the related field. Thus, a simple hierarchy is used, where the alternatives are constructed in one level.

Step 3. The pairwise comparisons are created.
Priorities are evaluated by a pairwise comparison matrix (PCM) on a scale. In Appendices A and B, the computing process is illustrated through an example.

Step 4. The consistency of the matrix is checked.
The consistency of the matrix is to be examined by the Consistency Index (*CI*), where the Consistency Ratio (*CR*) should be less than 0.1. In Appendices A and B, the computing process is illustrated through an example.

Step 5. The scores are derived.
In the next step the scores are derived, i.e., computing the weights of mobility alternatives for every evaluator in all groups by using formula 3.

Step 6. The weights for each group are aggregated by utilizing the geometric mean to get the final weight vectors.
The total number of pairwise comparisons for the first group is $n*(n-1)/2 = 15$, where $n=6$. After aggregating 26 responses, the results are as presented in Table 5.

Table 5. The weights for mode choice alternatives by using the AHP method for Group 1

Mode choice	PT	Car	Car-Pooling	Walking	Bike	H. Office
Final weight	0.3722	0.2329	0.0479	0.1407	0.0818	0.1245
Ranking	1	2	6	3	5	4

The total number of pairwise comparisons for the second group is $n*(n-1)/2 = 10$, where $n=5$. After aggregating 21 responses, the results are as presented in Table 6.

Table 6. The weights for mode choice alternatives by using the AHP method for Group 2

Mode choice	PT	Car	Car-Pooling	Bike	H. Office
Final weight	0.4386	0.2834	0.0527	0.1401	0.0852
Ranking	1	2	5	3	4

The total number of pairwise comparisons for the third group is $n*(n-1)/2 = 10$, where $n=5$. After aggregating 9 responses, the results are as presented in Table 7.

Table 7. The weights for mode choice alternatives by using the AHP method for Group 3

Mode choice	PT	Car	Car-Pooling	Bike	H. Office
Final weight	0.4304	0.2584	0.0530	0.1025	0.1557
Ranking	1	2	5	4	3

The CR for all evaluated pairwise comparison matrices of the AHP varies between the acceptable thresholds.

4.2 The findings of the BWM
For implementing the BWM logic, the following short questionnaire is created.

- “How long do you travel to work from your home?”
- “Please select the best and worst mobility types for commuting!”
- “Please evaluate other mobility types with respect to the best type using a scale of 1 to 9!”
- “Please evaluate other mobility types with respect to the worst type using a scale of 1 to 9!”

The main steps of BWM are the following:

Step 1. Identifying the alternatives.
When identifying the set of alternatives, in our study, the commuting alternatives are selected by experts in the related field taking into consideration the distance for each group (for Group 1 there are 6 alternatives, for Group 2 and 3 there are 5 alternatives).

Step 2. Defining the best and the worst alternatives of different mobility type by the simple scoring of the participating experts.

Step 3. Evaluation of the pairwise comparisons
Evaluating the pairwise comparisons between the best alternative and other mobility types by using a scale of 1 to 9, where 1 means “equal importance”, and 9 means “extremely more important”.

In the model of this study, $n = 6$ since six alternatives are compared for Group 1, whole, for Group 2 and 3 only five alternatives are compared $n = 5$.

Step 4. Making pairwise comparisons between the worst mobility type and other mobility types.
For the comparison, a scale of 1 to 9, where 1 means "equal importance", and 9 means "extremely more important". In Appendices, the computing process is illustrated through an example.

Step 5. The weights of the groups are aggregated.
After computing the weights of mobility alternatives for every evaluator in all groups, the weights for each group are aggregated by utilizing the geometric mean to get the final weight vectors. In Appendices, the computing process is illustrated through an example.

The total number of pairwise comparisons for the first group is *2n-3 = 9*, where *n=6*. After aggregating 26 weight vectors generated from 26 responses, the results are as presented in Table 8.

Table 8. The weights for mode choice alternatives by using the BWM method for Group 1

Mode choice	PT	Car	Car-Pooling	Walking	Bike	H. Office
Final weight	0.4861	0.1991	0.0418	0.0992	0.0745	0.0993
Ranking	1	2	6	3	5	4

The total number of pairwise comparisons for the second group is *2n-3 = 7*, where *n =5*. After aggregating 21 weight vectors generated from 21 responses, the results are as presented in Table 9.

Table 9. The weights for mode choice alternatives by using the BWM method for Group 2

Mode choice	PT	Car	Car-Pooling	Bike	H. Office
Final weight	0.4601	0.2918	0.0481	0.1167	0.0833
Ranking	1	2	5	3	4

The total number of pairwise comparisons for the third group is *2n-3 = 7*, where *n=5*. After aggregating 9 weight vectors generated from 9 responses, the results are as presented in Table 10.

Table 10. The weights for mode choice alternatives by using the BWM method for Group 3

Mode choice	PT	Car	Car-Pooling	Bike	H. Office
Final weight	0.5141	0.2074	0.0451	0.0778	0.1556
Ranking	1	2	5	4	3

Step 6. The CR is computed to check the consistency of the comparisons (Rezaei, 2016).
In Appendices, the computing process is illustrated through an example.

The CR for all evaluated pairwise comparison matrices for each evaluator of the BWM varies between the acceptable thresholds.

4.3 The findings of the BWM and the results of the AHP

The results of applying the AHP and the BWM methods are represented in Figure 4 and Figure 5. For the first group (presented in orange), to calculate the final weights based on the AHP approach, 390 (*26*15*) pairwise comparisons are calculated. However, to implement the BWM approach, solely 234 (*26*9*) pairwise comparisons are conducted. Considering both approaches, the figures present the alternatives' scores in the first group. Both approaches show that PT is the most used type followed by Car. The least used type is Car-Pooling followed by Bike mode.

For the second group (presented in yellow), to calculate the final weights based on the AHP approach, 210 pairwise comparisons are conducted. However, to implement the BWM approach, solely 147 pairwise comparisons are calculated. The figures present the alternatives' scores in case of the second group while taking both approaches into consideration. The results of both approaches highlight the PT mode as the most used type for the second group thus the same as for the first group. On the other hand, the least used type is Car-Pooling followed by the Home. Office option.

For the third group (presented in green), to calculate the final weights based on the AHP approach, 90 pairwise comparisons are made. However, to implement the BWM approach, solely 63 pairwise comparisons are conducted. The figures present the adopted results for the third group based on the AHP and the BWM approaches. The results of the third group demonstrate a slight difference compared with the second group. In case of the third group, both approaches highlight the PT type as the most used type followed by Car. On the other hand, the least used type is Car-Pooling followed by Bike mode.

The derived scores from the BWM are highly reliable as this method provides more consistent comparisons than the AHP approach. In the AHP, CR is a measure to check if the comparisons are reliable or not; in the BWM, CR is rather used to get the level of reliability because the output of the BWM is always consistent. The priority ranking outcomes for both the AHP and the BWM are the same; however, a slight difference can be detected in the obtained weight scores. An example of calculation process for both methods are presented in Appendices A and B.

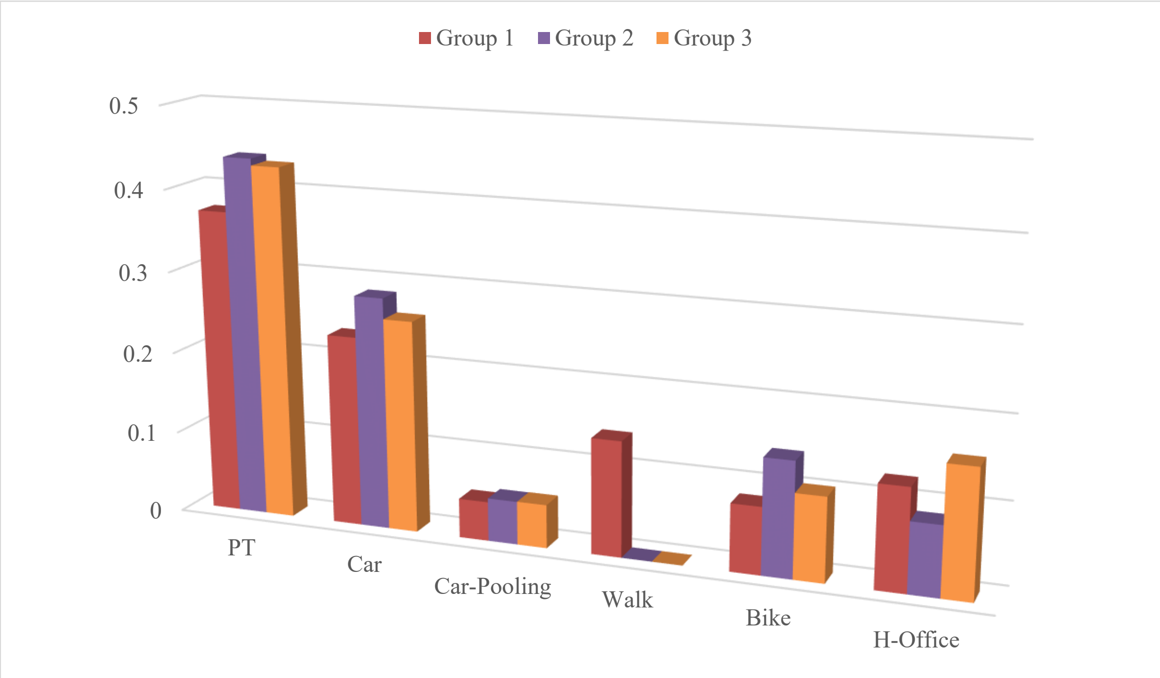

Figure 4. The final generated weights of the mode choice alternatives for all groups in case of using the AHP

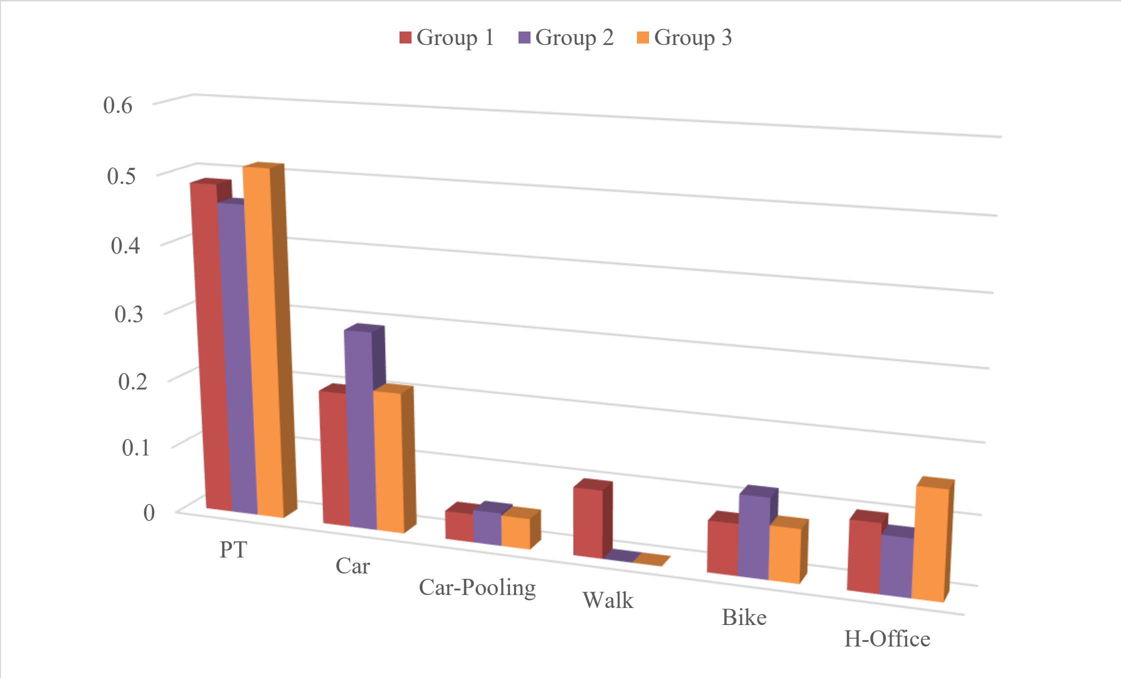

Figure 5. The final generated weights of the mode choice alternatives for all groups in case of using the BWM

4.4 A comparison of the obtained findings

We calculated the Spearman's rank correlation on BWM and AHP rankings. The R value is 0.9428, which is very close to plus one, representing a very high positive correlation. This result is a sign of the efficiency of the BWM approach. All priorities show very high concordance, for Group 1 the top positions are almost the same except for a change in the third and fourth rank (Table 11).

Table 11. Spearman's rank correlation coefficient for Group 1

Alternatives	Rank of AHP	Rank of BWM	d_i	$(d_i)^2$
PT	1	1	0	0
Car	2	2	0	0
Car-Pooling	6	6	0	0
Walk	3	4	-1	1
Bike	5	5	0	0
H. Office	4	3	1	1
m =6		R = 0.9428		

For Group 2 and 3 it can be said that the comparison of the AHP and BWM results are very successful, since the two rankings correlate strongly (Table 12 and Table 13).

Table 12. Spearman's rank correlation coefficient for Group 2

Alternatives	Rank of AHP	Rank of BWM	d_i	$(d_i)^2$
PT	1	1	0	0
Car	2	2	0	0
Car-Pooling	5	5	0	0
Bike	3	3	0	0
H. Office	4	4	0	0
m =5		R = 1		

Table 13. Spearman's rank correlation coefficient for Group 3

Alternatives	Rank of AHP	Rank of BWM	d_i	$(d_i)^2$
PT	1	1	0	0
Car	2	2	0	0
Car-Pooling	5	5	0	0
Bike	4	4	0	0
H. Office	3	3	0	0
m =5		R = 1		

5. Discussion

Based on the gained results, it can be stated that the simultaneous application of the AHP and the BWM validates the applicability of both MCDM techniques to mode choice analysis. Considering the identical evaluator sample and the different survey procedure and time, the outcomes of the two models are surprisingly similar, to such extent that there is absolutely no difference in the final ranking for each group. Obviously, the final weights scores (or rather alternative scores) alter minimally in the two techniques, but this can be verified by the nature of the different approaches. The AHP covers all possible pairwise comparisons, while the BWM focuses on the comparison with the best and the worst alternative alone, all other pairs are omitted. Although the sample with altogether 56 expert evaluators is small, for all groups (i.e., short, middle, and long-distance commuters), the final ranking of modes becomes the same for the AHP and for the BWM.

For short-distance commuters (Group 1), the dominancy of the PT is clear (0.3722 with the AHP and even higher, 0.4861 with the BWM) even by considering the alternatives of walking and bike. This outcome sheds light on the significance of the PT system in the urban environment. As the cluster is created for up to 10 km commuting distance, the fifth position of the bike mode is definitely surprising. It has to be emphasized that cultural characteristics might play a significant role in this result as in some big cities of Western Europe, biking could be more popular for commuting. In addition, the lack of safe and connected infrastructure may cause some discomfort, when choosing bike as a transport mode. In Mersin there are some bike routes, but they are not organized in a comprehensive bike network. However, it has to be noted that the city is located at the seaside in a relatively flat area with suitable weather conditions, which are considered as enablers for bike usage. Thus, it can be stated that in case of sufficient infrastructural investments the modal share of biking could be significantly enhanced.

Group 2 represents the commuters from 10 to 40 km distance. PT receives the highest score followed by the use of private cars, which is a rather expected outcome for this range. An expected result is the low representation of car-pooling. Studies in the past have shown that in particular from the perspective of feeling and emotions, only limited numbers of commuters in practice are inclined to adopt car-pooling (Bulteau et al., 2019). The findings in the paper seem to confirm this picture. Interestingly, home office does not raise the attention of the respondents of this group. It must be emphasized that the survey was conducted before the COVID-19 pandemic situation, which has a serious impact on the mode choice preferences and on the preference (and technological possibility) of home office solutions, too.

Respondents who travel a lot to their workplaces (Group 3) position PT on the first and private car on the second place. Note that the largest difference between the BWM and the AHP models' outcomes can be detected while evaluating PT in Group 3. The BWM allocates the weight value of 0.5141, while in case of the AHP, it is 0.4386, which is smaller. However, the unquestionable dominance of PT over all other transportation modes can be seen. As expected, the preference of home office reaches the largest value in this cluster of evaluators, but its extent (0.1556) is smaller than expected. Again, it must be stressed that cultural characteristics and the structure of economy might have serious impact on the survey outcomes. Car-pooling is set as last like in all cases. However, for this long range of commuting, car-pooling might be a flexible and cheap solution in comparison with private car usage.

It has to be noted that the data collected and analyzed is preference data. This means that actual travel behavior and final choices cannot be directly captured by this method. However, the method is suitable to estimate the general preferences of the travelers. In addition, more research should be conducted to compare the two methods and include other methods in terms of predictable power for actual behavior.

A major part of the results is expected, such as the dominance of PT for the three commuter clusters and the second position of private car use among the possible choice alternatives. However, two significant novelties can be identified based on the final outcomes of the AHP and the BWM analysis.

First, the low representation of car-pooling even for the mid- and long-distance commuter groups is remarkable and the characteristics of the evaluators is dominant in this result. It seems advisable to launch a targeted campaign on the possibility and benefits of this recent mobility type.

Furthermore, the role of home office is still controversial based on the mobility choice preferences of the clustered respondent sample. Even the commuters over 10 km distance are not keen on choosing home office for the whole week (i.e., doing home office for only some days is not common among the alternatives). This phenomenon might change due to the recent COVID-19 pandemic situation; thus, further investigations are recommended in this domain.

We strongly emphasize that the presented results should be considered with the observation that the pattern of the university students and staff is rather specific with the dominance of young and single people who do not necessarily have own cars. However, it has to be also considered that in many cities the existence of universities has serious impact on commuting travel patterns and on the whole transport system of the city. Consequently, it is highly relevant to acquire information on commuting preferences of this specific group of commuters. As demonstrated, the applied MCDM models can be considered as suitable methods to conduct this type of survey.

6. Conclusion

The main objective of this paper is to examine the applicability of two MCDM methods for mode choice analysis. Since the AHP and the BWM present exactly the same ranking in the offered mode choice for all three groups of respondents and indicate solely a slight difference in the final weight scores of commuting transport types, the experiment can be considered successful. Moreover, our presented models have practical relevance from the perspective of data collection by saving time and cost in the survey procedure that can be reached by the smaller pattern and the less effort required from the respondents.

In the long term, this result might have a significant impact on the theory and practice of mode choice analysis. Provided representative citizen surveys can be conducted by using MCDM questionnaires with survey instructors or even by mobile apps involving commuters or other PT passengers, the survey data and their analysis might contribute largely to transport planning. Based on the presented results in this paper, especially the tested AHP and BWM techniques targeting the direct comparisons of commuting mobility types are very promising as survey models. The easy and quick evaluation, the relative high consistency, and the clear potential of analysis are emphasized as benefits in case of both examined methods with the slight priority of the BWM over the AHP.

Practically, in the early phase of a transport planning process, the preference survey (either by AHP or BWM) can be conducted more easily with less cost and time along with higher response consistency, compared to the traditional big pattern methods. Furthermore, the existing transport development scenarios gained by different methods can be further sophisticated by the MCDM results. Thus, the extension of the set of mode choice analysis methodologies enriches the practice of transport planning, which might lead to a more appropriate transport policy making.

As a limitation of the research, the lack of flexibility must be highlighted. The evaluators do not have the option to change the offered transport modes nor to nominate a new form of commuter type, both the AHP and the BWM are not capable of handling this possibility. Another important note is that all respondents were selected from the set of university students or staff, and thus, the conclusions drawn from the responses must be treated cautiously and should only be referred in the context of university employees and students. Also, a comparative study between our results and the outcomes of traditional methods, e.g., SEM or SAW could provide added value, but that would require another survey on a large-scale pattern. Unfortunately, no available data about travel pattern were be found in the case of the location, thus the comparison with observational data is not really possible. In the future it is intended to find or create a reliable database for urban mobility in the city of Mersin.

For future research, it is recommended to create and apply another MCDM model by using the techniques of TOPSIS, MACBETH, ELECTRE, or PROMETHEE. Even though Structural Equation Modeling is a well-proven and relevant tool of the operations research methodology, it is not the only possible way for mode choice analysis. The group of MCDM techniques can contribute and make serious impacts on investigating the preferences and motivations of commuters or other travelers in urban environment.

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Appendices

Appendix A

The following steps are required to conduct the AHP method:

Step 1. We define the mobility types to be estimated and the related criteria and alternatives. In our case, 6 alternatives are created (A, B, C, D, E, F).

Step 2. The hierarchy structure in our case is constructed of 6 alternatives on one level, which is be defined by experts in the related field.

Step 3. The PCMs of the alternatives are constructed by a quadratic and reciprocal matrix. We create the PCM as shown in Table A1, then the respondents conduct the evaluations by using Table 1. After the evaluations the values of Table A2 are created.

Table A1. AHP example

	A	B	C	D	E	F
A	1	A related to B	A related to C			
B	B related to A	1				
C			1			
D				1		
E					1	
F						1

Table A2 The evaluated pairwise comparison matrix

	A	B	C	D	E	F
A	1,0000	3,0000	1,0000	4,0000	5,0000	3,0000
B	0,3542	1,0000	0,5833	0,3542	2,0000	0,5833
C	1,0000	2,0000	1,0000	2,0000	3,0000	3,0000
D	0,2583	3,0000	0,5833	1,0000	3,0081	2,0000
E	0,2042	0,5833	0,3542	0,5833	1,0000	0,5833
F	0,3542	2,0000	0,3542	0,5833	2,0000	1,0000

Step 4. The consistency of the matrix is examined by the Consistency Index (*CI*) and Consistency Ratio *(CR) < 0.1.* In our example the size of the comparison matrix is *n=6*. The largest eigenvalue is equal to the size of the comparison matrix $\lambda max = 6.5964$.

$CI = \frac{6.5964-6}{6-1} = 0.1193$ we get this value by applying formula (1).

The random consistency index of our example is *RI=1.24* from Table 2.

Then, $CR = CI/CR = \frac{0.1193}{1.24}$ $\boldsymbol{= 0.0962 < 0.1}$ we get this value by applying formula (2). The value here is smaller than 0.1 and the consistency is acceptable. If we would get a value of $CR > 0.1$ then we would have to revise the subjective judgment.

Step 5. In the next step the weights of alternatives for the evaluators are computed using formula (3). We take the sum of each column in order to generate the normalized matrix (Table A3).

Table A3 Sum of each column to derive the weights

	A	B	C	D	E	F
A	1,0000	3,0000	1,0000	4,0000	5,0000	3,0000
B	0,3542	1,0000	0,5833	0,3542	2,0000	0,5833
C	1,0000	2,0000	1,0000	2,0000	3,0000	3,0000
D	0,2583	3,0000	0,5833	1,0000	3,0081	2,0000
E	0,2042	0,5833	0,3542	0,5833	1,0000	0,5833
F	0,3542	2,0000	0,3542	0,5833	2,0000	1,0000
Sum	3,1708	11,5833	3,8750	8,5208	16,0081	10,1667

Step 6. We calculate the normalized matrix (Table A4) by deriving each value of the evaluated pairwise comparison matrix by the sum of each column. Following that, we derive the weights for each alternative by taking the geometric mean for each row.

Table A4 The normalized matrix

	A	B	C	D	E	F	Weight
A	0,3154	0,2590	0,2581	0,4694	0,3123	0,2951	0,3154
B	0,1117	0,0863	0,1505	0,0416	0,1249	0,0574	0,1117
C	0,3154	0,1727	0,2581	0,2347	0,1874	0,2951	0,3154
D	0,0815	0,2590	0,1505	0,1174	0,1879	0,1967	0,0815
E	0,0644	0,0504	0,0914	0,0685	0,0625	0,0574	0,0644
F	0,1117	0,1727	0,0914	0,0685	0,1249	0,0984	0,1117

Appendix B

The following steps are required to conduct the BWM method:

Step 1. Identifying the set of alternatives, in our example we consider 6 alternatives (A, B, C, D, E, F).

Step 2. Defining the best and the worst alternatives, where the evaluator selects the best alternative (Table A5) and the worst alternative (Table A6).

Table A5 Selecting the best mobility type

Mobility Type	A	B	C	D	E	F
Best Mobility Type: A						

Table A6 Selecting the best mobility type

Mobility Type	A	B	C	D	E	F
Worst Mobility Type: C						

Step 3. Evaluating the PCMs between the best mobility type and other mobility types by using a scale of 1 to 9, where 1 means “equal importance”, and 9 means “extremely more important”. In our example A is the best alternative (Table A7).

Table A7 Evaluating all mobility types comparing to the best mobility type

Mobility Type	A	B	C	D	E	F
Best Mobility Type: A	1	3	9	4	6	2

Step 4. Evaluating the PCMs between the worst mobility type and other mobility types by using a scale of 1 to 9, where 1 means "equal importance", and 9 means "extremely more important". In our example A is the worst alternative (Table A8).

Table A8 Example of evaluating all mobility types comparing to the worst mobility type

Mobility Type	A	B	C	D	E	F
Worst Mobility Type: C	9	7	1	5	3	5

Step 5. We demonstrate the detailed calculation of mobility type alternatives' scores for this example $w = \{w_1, w_2, w_3, w_4, w_5, w_6\}$ computed by applying the BWM method (formula 7).

min ξ^* s.t.

$w_1 - 1w_1 \leq \xi^*$

$w_1 - 3w_2 \leq \xi^*$

$w_1 - 9w_3 \leq \xi^*$

$w_1 - 4w_4 \leq \xi^*$

$w_1 - 6w_5 \leq \xi^*$

$w_1 - 2w_6 \leq \xi^*$

$w_3 - 7w_2 \leq \xi^*$

$w_3 - 5w_4 \leq \xi^*$

$w_3 - 3w_5 \leq \xi^*$

$w_3 - 5w_6 \leq \xi^*$

$w_1 + w_2 + w_3 + w_4 + w_5 + w_6 = 1$

$w_1 \geq 0, w_2 \geq 0, w_3 \geq 0, w_4 \geq 0, w_5 \geq 0, w_6 \geq 0.$

The weight scores for this specific evaluation are the following normalized values.

$w = \{0.3844, 0.1551, 0.0337, 0.1163, 0.0775, 0.2327\}$

The consistency index (CI) for this problem is 3 (see Table 3), and the consistency ratio is computed by using formula (8). CR is 0.1097, which implies a good consistency.

CR= $\xi^* / \text{Consistency Index}$ = 0.3291/3 =0.1097