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Application of grey analytic hierarchy process to estimate mode choice alternatives: A case study from Budapest

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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 proposes a multi-criteria decision-making approach using the grey theory to analyze mode choices. An extended analytic hierarchy process (AHP) model, which combines the advantages of the classic AHP and the grey theory for the accurate estimation of the commuting mode weight coefficients, is applied to a real transportation problem involving evaluators. The presented approach is applied for a real-life case study in Budapest. Based on the results, for all distances, public transport is ranked first followed by the car mode; however, for short- and mid-distance commuters, home office and bike might be suitable options, too. The results of this method are compared with the fuzzy AHP method. Having the same ranking in case of the two analyses means that the proposed method provides correct results under uncertainty in a group decision-making process. Thus, the outcomes highlight the applicability of the proposed method to the evaluation of mode choice.

Introduction

Undeniably, travelers' mode choices became one of the most vital issues of transport planning in the last decades. In the scientific literature, two fundamental approaches exist in parallel: the statistical based and the multi-criteria decision-making (MCDM) methodologies. The conventional statistical techniques as well as the recently emerged machine learning models aim to understand the data structure provided by measured or simulated passenger movements (Zhao et al., 2020), while the MCDM models consider mode choice as a decision on the alternative mobility types and analyze the group preferences for these alternatives (Fierek and Zak, 2012). Several researchers try understanding the decision process of the transport mode choice and suggest appropriate interventions to achieve sustainable mobility (Lakatos and Mándoki, 2021). The trend of using MCDM solutions requires integrated tools and approaches (Chanthakhot and Ransikarbum, 2021).

The scientific debate on the superiority of these two basic approaches is ongoing; however, within each set of approaches, there have been many attempts to prioritize the available mode choice techniques from the aspect of their prediction efficiency.

In the circle of statistical based models, machine learning can outperform the conventional logit models in terms of its predictive capability (Cheng et al., 2019; Lindner et al., 2017; Wang and Ross, 2018; Zhang and Xie, 2008). The logit models provide higher behavioral soundness, but this trade-off should be handled when choosing between the models (Zhao et al., 2020).

In the cluster of MCDM techniques, the basis of the comparison is generally the consistency of the evaluations (Aguarón et al., 2021), the efficiency of the survey process in terms of response rate, evaluation time, and the total number of responses (Broniewicz and Ogrodnik, 2020), or the decision-makers' satisfaction with the ultimate priority ranking (Macharis and Bernardini, 2015). Consequently, those types of MCDM models can be considered more accurate which provide high consistency in the responses along with the simplification of the survey process and contain consensus creation, negotiation, or a follow-up of the results.

Owing to mode choice analysis, in-depth qualitative interviews are generally conducted (Schneider, 2013) on a representative pattern of urban citizens. These interviews are highly time-consuming and require a lot of efforts from the respondents since detailed questions are asked on the economic, social, and environmental attributes of the potential and real passengers (Clifton and Handy, 2001; Gardner and Abraham, 2007). Evidently, long questionnaires deter respondents from completing; thus, the response rate drops, and the representativity of the

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survey might be secured solely by high survey cost or long procedure time.

Consequently, in transport planning and mode choice analysis, researchers strive to create such models which reduce the requirements for involving several laymen as respondents, but they are still capable of deep analysis (Deng and Nelson, 2012; Losada-Rojas et al., 2019; Tang et al., 2020). The analytic hierarchy process (AHP) combines several benefits; thus, it is one of the most popular modeling techniques in transport planning (Ransikarbum et al., 2021; Ransikarbum and Leksomboon 2021). Even if the number of pairwise comparisons to be evaluated is large in case of multi-level decision, hierarchy and reasonable reduction might be necessary (Abastante et al., 2019; Duleba, 2020; Duleba and Moslem, 2021; Moslem et al., 2020). The AHP has already been used to evaluate the motivating factors in case of cycling (Majumdar et al., 2020) and to identify the physical characteristics of sidewalks (Shafabakhsh et al., 2015), but specifically for mode choice analysis, it has been rarely applied.

In the current paper, an extended AHP model for mode choice analysis and its application on a real transportation problem involving evaluators from the Hungarian capital, Budapest, are introduced. The created model is based on the grey analytic hierarchy process (grey AHP), which combines the advantages of the classic AHP and the grey theory for the accurate estimation of the commuting travel modes' weight coefficients (Sahoo et al., 2017; Moslem and Çelikbilek, 2020). The benefit of the grey approach over the conventional statistical methods is that the grey models solely require a limited amount of data to estimate the system behavior including the mode selection by attributes or by preference and obtain an unbiased final result (Zeng et al., 2017). These advantages make the proposed model of the current research fit in all sense for the requirements of mode choice analysis: it requires low effort from the respondents, it is trustworthy and consistent, as well as it makes the in-depth analysis on the selection of travel modes possible.

The theoretical contribution of the current research is the extension of the possible mode choice analysis tools by a method which is not only capable of considering the vagueness of participant responses, but requires low computational time, as well. In addition, the new method is compared to the well-proven fuzzy AHP method, where comparing the results can be considered as a justification of applying the grey AHP. The demonstrated model can be widely applied to support urban development planning by taking the classical and novel mobility types, e.g., carpooling and home office, into account. The selected case study is highly appropriate for this purpose since the municipality of Budapest is committed to promote new mobility solutions and open to receive suggestions from research communities.

In the following parts of the paper, first, the most relevant models for commuting mode choice analysis from the scientific literature are overviewed. Afterward, a detailed introduction of the grey AHP through the presentation of the AHP and grey theory is demonstrated. It is followed by the presentation of the real-world application of the grey AHP model for urban mobility evaluation in Budapest. Finally, conclusions are drawn, and further research along with some recommendations for the future appliers of the proposed model are demonstrated.

Literature review

Regarding sustainability, shifting commuters to public transport is an efficient policy . To understand the user requirements and what triggers changes in their travel behavior, the main priorities in transport mode choice should be explored. Jain et al. (2014) use the AHP method to identify some criteria. The researchers find that safety, reliability, cost, and comfort are the main factors influencing mode choice. Furthermore, the scholars state that most of the commuters will shift to public transport once a high level of service is provided. In the paper of Mayo and Taboada (2020), AHP is used to rank the factors affecting the commuters' transport mode choice in developing countries. The results show that safety is the first in the ranking, which is followed by accessibility, cost, and comfort. Interestingly, the environment factor receives the last place of the ranking. In another survey, Kumar and Ganguly (2018) prioritize those attributes that travelers consider important while deciding on the transport mode. The researchers use AHP for urban commuters in New York (USA) and in Delhi (India). It is revealed that safety and reliability are mostly preferred in the USA, while price is primarily relevant in India. Longo et al. (2015) focus on university students and staff when applying the AHP method for evaluation. Travel time, cost, comfort, safety, flexibility, and environment are included as criteria, while the provided transportation modes are public transport, bicycle, car-pooling, and walking. The results show that the most important criteria are the cost and the travel time, while the environment factor is not considered relevant. In terms of alternatives, bicycle and car-pooling are listed. Cielsa et al. (2020) use an MCDM process to choose the best sustainable transportation mode, where travel safety, travel time, travel comfort, travel cost, and weather conditions are examined. Travel time and travel cost have the highest weights. The method is applied to city bike, electric kick-scooter, electric scooter, and electric car. The results demonstrate that the city bike is the highest-ranked solution.

AHP can be considered as a flexible and powerful tool applied to understand and quantify user preferences. The AHP technique is used to analyze trade-offs among conflicting criteria. Ransikarbum et al. (2020) develop a model to enhance the practitioners' applications in decision-support systems. De Luca (2014) applies different criteria and indicators together with planning scenarios, which are the followings: no change in the status, increasing the frequency of public transport, the electrification of railway infrastructure, and regional integration. The results demonstrate that regional integration is the most preferred solution. Le Pira et al. (2015) collect preferences while analyzing sustainable mobility solutions. AHP is applied with considering such alternatives as public transport enhancement, changes in traffic management, the promotion of car-pooling, the introduction of dedicated bike-sharing services, and the encouragement of teleworking. Nalmpantis et al. (2019) assess innovative ideas for public transport by using AHP. The main reason for choosing this MCDM method is its unbiased hierarchy of the alternatives. Based on a survey of 97 experts, three criteria are considered in the following order: utility, feasibility, and innovativeness. The ideas are ranked based on this order, where the Mobility as a Service platform, the enhanced public transport service, the advanced journey planner, marketing, and e-ticketing are the most relevant solutions.

To define which method is the most suitable, it is useful to assess the frequently applied methods in the literature. Based on Mardani et al. (2015), AHP is by far the broadest used multi-criteria decision-making analysis method with 32%. In another literature review about the application of these methods in case of transportation related projects by Macharis and Bernardini (2015), it is found that AHP is applied in more than 30% of the assessed use cases. Khamhong et al. (2019) evaluate the criteria with a number of associated sub-factors related to the selection of the best alternative, where the results of the group decision analysis are provided by relative weights. Ransikarbum and Khamhong (2021) evaluate healthcare applications, where fuzzy AHP is used to assess the criteria considered important. During the evaluation of the preferences, information is received from both the technical experts and the user groups. Damidavičius et al. (2020) use various MCDM methods and find very similar overall results calculated by the applied methods when assessing urban mobility measures. However, when Sarraf and McGuire (2020) compare different methods in terms of route planning, the results show that AHP and fuzzy AHP have the best performance. The researchers claim that AHP is a good choice based on its simplicity, the ability to handle qualitative and quantitative data and to derive criteria weights.

Besides fuzzy AHP, the grey system approach is proven to be efficient. Based on the work of Liu et al. (2011), the theory can be applied to any kind of scientific problems where incomplete or inaccurate information is present. The scholars compare the effectiveness of the method with stochastic probability and fuzzy mathematics and find that the grey approach is well applicable to the weight clustering of variables. Bu et al. (2010) aim to overcome the obstacles of evaluation effectiveness for crime prevention systems. Therefore, a combination of AHP and grey clustering is proposed to guarantee the accuracy of the weight coefficients. The results show the feasibility and reliability of the model. In a similar way, Sahoo et al. (2016) combine the advantages of AHP and the grey clustering method to estimate the weight coefficients in the field of environmental management policies. The researchers claim that the application of the grey approach eliminates the dependency on the experience of experts. Baradaran (2017) uses the AHP approach based on the grey number scores to reduce uncertainty and incomplete information. The method is applied to evaluate incidents in urban railway systems and results in lower computational complexity. The grey AHP is used in several fields; however, it has no broad application in the field of transportation related issues yet.

When considering the structure of the survey supporting the analysis, some suitable solutions are available: a small set of experts or the general public can be interviewed. Ghorbanzadeh et al. (2018) assess sustainable urban transport planning with 97 evaluators, where besides the criteria, the participants' age, gender, and education are asked. Chowdhury et al. (2018) asks 363 users about integrated public transport systems as well as seven policymakers to define the weights of the attributes thus conducting the AHP process. The survey consists of the respondents' age, income, gender, public transport characteristics, and the attributes. In the work of Longo et al. (2015), socio-demographic information, trip features (e.g., the time of departure, mode choice), the evaluation of the model parameters, and possible suggestions are included. 3976 valid answers, including residents (60%) and commuters (40%), are collected, which can be considered as statistically significant. Cielsa et al. (2020) collect almost 3000 answers, where considering the age groups, students make up the majority. Regarding the trip distance, most respondents commute less than 20 km. In de Luca's survey (2014), 500 individuals, who are randomly selected to match the general census statistics, are asked. The participants have to answer pairwise comparisons. Jain et al. (2014) invite 10 local experts to create the categories and around 500 users to assess the factors related to mode choice.

Commuters have specific characteristics; therefore, their characteristics and preferences may be different. Mayo and Taboada (2020) analyze 191 responses and find that the travelers' age, employment status, and trip purpose influence the importance of the factors. In general, younger people consider the cost and the environment factors important, while older people think that comfort and safety are more crucial. At the same time, as a more decisive secondary factor, students indicate the cost, while employees consider the environment factor. In case of the trip purpose, for school trips, participants mark availability, while for business trips, they favor comfort. Ye and Titheridge (2017) collect 1364 answers. The results suggest differences in the respondents' socio-demographic characteristics related to the commuting modes, which means that car users tend to be from the older generation with high income, while bicycle users seem to be younger with a lower level of income. Guo et al. (2020) conduct a survey with 401 participants; from this sample, 64% live in the city, and 36% live in the agglomeration. The scholars find that the average commuting time is around 28 min, but it is slightly more in case of public transport and slightly less for bicycle users. From the literature review, the need to develop a novel model to define the mode choices can be deduced, which is realized in the current paper. A brief comparison of the literature given in this section and the current study is presented in Table 1 to highlight the differences among the studies.

Methodology

The basis of the classic AHP was first introduced by Saaty in 1977

Table 1
A brief comparison of the literature.

Reference	Method	Problem	Evaluation		Result		GroupDM
			Fuzzy/Grey Number	Crisp Number	Fuzzy/Grey Number	Crisp Number	
Jain et al., 2014	Conventional AHP	Mode Choice		✔		✔	✔
Mayo and Taboada, 2020	Conventional AHP	Mode Choice		✔		✔	✔
Kumar and Ganguly, 2018	Conventional AHP	Mode Choice		✔		✔	✔
Longo et al., 2015	Conventional AHP	Mobility Management		✔		✔	✔
Cielsa et al., 2020	MCDM Model	Mobility Management		✔		✔	✔
Ransikarbum et al., 2020	Conventional AHP and Multi Objective Optimization	Additive Manufacturing Scheduling		✔		✔	
De Luca, 2014	Conventional AHP	Transportation Planning		✔		✔	✔
Le Pira et al., 2015	Conventional AHP	Sustainable Mobility Solutions		✔		✔	✔
Nalmpantis et al., 2019	Conventional AHP	Public Transport Innovations		✔		✔	✔
Chowdhury et al., 2018	Conventional AHP	Public Transport Users' Perceptions		✔		✔	✔
Khamhong et al., 2019	Fuzzy based AHP	3D Printer Selection	✔			✔	✔
Ransikarbum and Khamhong, 2021	Fuzzy based AHP + TOPSIS	Additive Manufacturing Printer Selection	✔			✔	✔
Damidavičius et al., 2020	COPRAS + TOPSIS + ARAS + EDAS	Sustainable Mobility Measures		✔		✔	✔
Sarraf and McGuire, 2020	Conv. and Fuzzy based MCDM	Safe Route Planner	✔	✔		✔	✔
Bu et al., 2010	Conventional AHP + Grey Clustering	Evaluation For Crime Prevention System		✔		✔	✔
Sahoo et al., 2016	Conventional AHP + Grey Clustering	Groundwater Potential Zone Delineation		✔		✔	✔
Baradaran, 2017	Grey based AHP	Risks of Urban Rail Transportation	✔			✔	✔
Ghorbanzadeh et al., 2018	Interval AHP	Sustainable Urban Transport Planning	✔			✔	✔
He and Titheridge, 2017	Statistical Methods	The Role of Travel Mode Choice on Satisfaction		✔		✔	✔
Guo et al., 2020	Statistical Methods	Mode Choice		✔		✔	✔
Current study	Grey AHP	Mode Choice	✔	✔	✔	✔	✔

(Saaty, 1977). The proposed grey AHP process is derived from the studies of Zareinejad et al. (2014) and Çelikbilek (2018) and applied to evaluate urban mobility types for a case study from Budapest. The proposed evaluation methodology is primarily a combination of the grey theory and AHP. In some situations of decision-making problems like mode choice analysis, uncertain information and complexity can be more than for other problems. These can complicate the problem and solution process. Additionally, it is possible that some decision-makers cannot make their evaluations with clear comparisons, or some types of problems do not allow this. For example, two people can describe the weather as too hot at the same time. But we can never be sure at which degree they start to describe the weather as too hot, as well as their description degree of the too hot is unknown, too. These grey number applications with the MCDM problems are very useful for the group decision-making process with multiple decision-makers, which is used to decrease the decision-makers' subjectivity as another variety of uncertainty.

The steps for the evaluation of mobility types are provided below and depicted in Fig. 1.

Step 1: Defining the Aim and the Alternatives: Solving AHP problems starts with defining the aim then the factors and the alternatives related to the aim of constructing the hierarchy tree.

Step 2: Constructing the Hierarchical Structure: The hierarchical structure of the problem is constructed by using the aim, the alternatives, and the factors of the problem. In this case, there are exclusively those alternatives that are related to the aim. Thus, the hierarchical structure has two levels (see Fig. 2).

Step 3: Obtaining the Grey Pairwise Comparisons: In this step, the alternatives of the aim are compared in pairs as in the classic AHP. However, linguistic scales given in the following table (Table 2) are used instead of the crisp scales of the classic AHP. The grey number representations of the linguistic scales are provided in Table 2, as well. The grey number, which is described as a number whose certain value is unknown, but its potential value set is known, is the true expression of the grey uncertainty, like fuzzy set, rough set, or interval number (Xie and Liu, 2015). Namely, grey numbers can be used to express the uncertainty of subjective judgements, especially in group decision-making. For example, [4,6] grey number means that 4 is the lower limit and 6 is the upper limit.

As an example, the pairwise comparison of expert *e* is given in

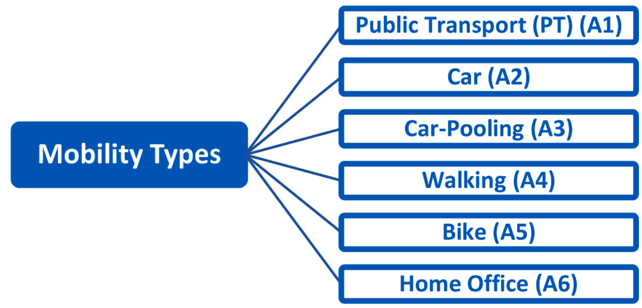

Fig. 2. The hierarchical structure of the mobility types.

Table 2
Linguistic scales and the grey numbers used for the pairwise comparisons of the grey AHP.

Importance value	Linguistic scale	Grey number
1	Equally Important	[1,2]
3	Weakly Important	[2,4]
5	Important	[4,6]
7	Strongly Important	[6,8]
9	Absolutely Important	[8,10]

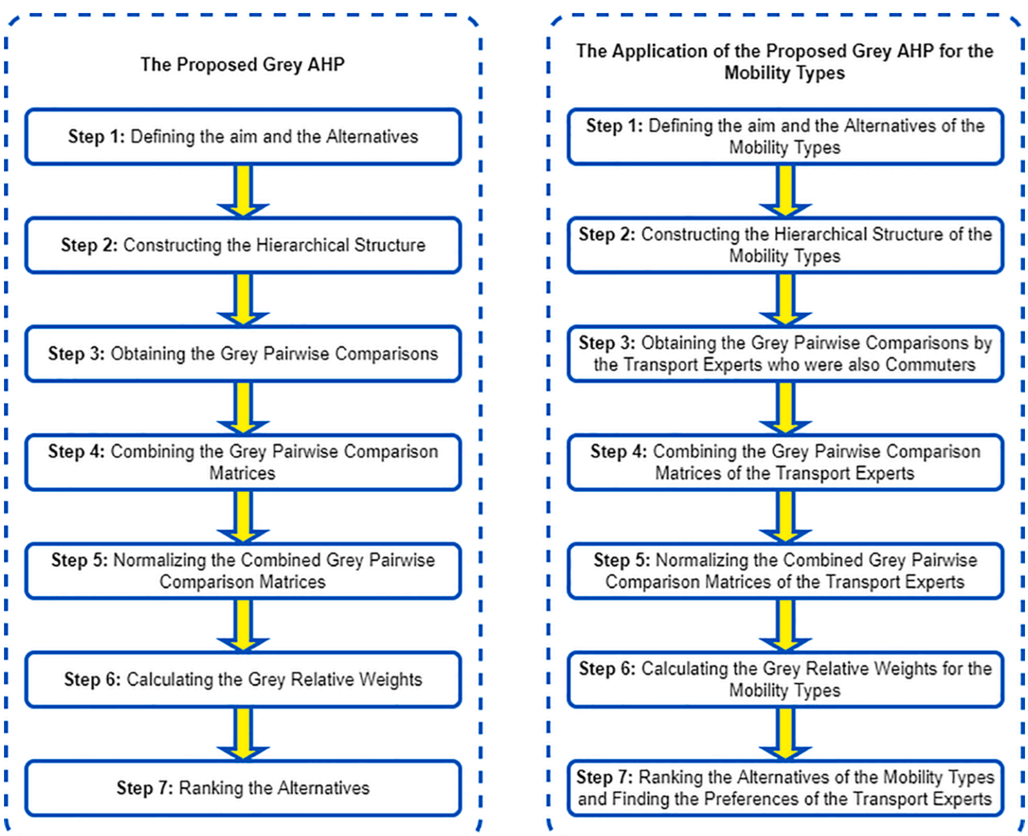

Fig. 1. The framework of the proposed grey AHP approach and its application in this study.

Equation (1). $\otimes X_{ij}^e, = \left[\underline{X}_{ij}^e, \overline{X}_{ij}^e\right]$ represents the pairwise comparison of the ith criterion and jth criterion done by expert e. The main diagonals of the pairwise comparisons are filled with $[1,1]$, as given in Equation (2), and the upper parts of the main diagonals are filled by using the opposite forms of the multiplication operation of the pairwise comparisons at the lower parts of the main diagonals, as given in Equation (3).

$$D^e = \begin{bmatrix} \otimes X_{11}^e & \otimes X_{12}^e & \cdots & \otimes X_{1j}^e & \cdots & \otimes X_{1n}^e \\ \otimes X_{21}^e & \otimes X_{22}^e & \cdots & \otimes X_{2j}^e & \cdots & \otimes X_{2n}^e \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ \otimes X_{i1}^e & \otimes X_{i2}^e & \cdots & \otimes X_{ij}^e & \cdots & \otimes X_{in}^e \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ \otimes X_{n1}^e & \otimes X_{n2}^e & \cdots & \otimes X_{nj}^e & \cdots & \otimes X_{nn}^e \end{bmatrix} \tag{1}$$

$$\otimes X_{ii}^e = [1, 1] \tag{2}$$

$$\otimes X_{ij}^e = \left[\frac{1}{\overline{X}_{ij}^e}, \frac{1}{\underline{X}_{ij}^e}\right] \tag{3}$$

Step 4: Combining the Grey Pairwise Comparison Matrices: All pairwise comparisons of the experts are combined by using Equation (4), which is a geometric mean formulation like the classic AHP.

$$\otimes X_{ij} = \sqrt[D]{\prod_{d=1}^{D} \otimes X_{ij}^d} \tag{4}$$

The difference in this case is that the geometric means are calculated for the upper parts and the lower parts separately. After the combination of the experts' pairwise comparison, the main pairwise comparison matrix D, as given in Equation (5), is obtained.

$$D = \begin{bmatrix} \otimes X_{11} & \otimes X_{12} & \cdots & \otimes X_{1j} & \cdots & \otimes X_{1n} \\ \otimes X_{21} & \otimes X_{22} & \cdots & \otimes X_{2j} & \cdots & \otimes X_{2n} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ \otimes X_{i1} & \otimes X_{i2} & \cdots & \otimes X_{ij} & \cdots & \otimes X_{in} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ \otimes X_{n1} & \otimes X_{n2} & \cdots & \otimes X_{nj} & \cdots & \otimes X_{nn} \end{bmatrix} \tag{5}$$

Step 5: Normalizing the Combined Grey Pairwise Comparison Matrices: The normalization of the pairwise comparison matrix is calculated by using Equation (6) and Equation (7) to obtain the normalized pairwise comparison matrix given in Equation (8).

$$\underline{X}_{ij}^* = \left[\frac{2\underline{X}_{ij}}{\sum_{i=1}^n \underline{X}_{ij} + \sum_{i=1}^n \overline{X}_{ij}}\right] \tag{6}$$

$$\overline{X}_{ij}^* = \left[\frac{2\overline{X}_{ij}^*}{\sum_{i=1}^n \underline{X}_{ij} + \sum_{i=1}^n \overline{X}_{ij}}\right] \tag{7}$$

$$D^* = \begin{bmatrix} \otimes X_{11}^* & \otimes X_{12}^* & \cdots & \otimes X_{1j}^* & \cdots & \otimes X_{1n}^* \\ \otimes X_{21}^* & \otimes X_{22}^* & \cdots & \otimes X_{2j}^* & \cdots & \otimes X_{2n}^* \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ \otimes X_{i1}^* & \otimes X_{i2}^* & \cdots & \otimes X_{ij}^* & \cdots & \otimes X_{in}^* \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ \otimes X_{n1}^* & \otimes X_{n2}^* & \cdots & \otimes X_{nj}^* & \cdots & \otimes X_{nn}^* \end{bmatrix} \tag{8}$$

Step 6: Calculating the Grey Relative Weights: The relative weights are calculated by using the normalized pairwise comparison matrix and Equation (9). The obtained relative weights are with grey numbers, too.

$$W_i = \frac{1}{n}\sum_{i=1}^{n} \left[\underline{X}_{ij}^*, \overline{X}_{ij}^*\right] \tag{9}$$

Step 7: Ranking the Alternatives: The relative weights used as final weights in this study are ranked from the highest to the lowest. The best alternative is the one with the highest weight, and the worst alternative is the one with the lowest weight.

Results

As a real-life case study, a survey is conducted with 56 evaluators as the total sample, where the participants' travel distances are between 0.1 and 50 km. In the frames of a project entitled MOVECIT, from 2016 to 2019, responses from transport experts, who were commuters themselves, on the mode choice preferences in the Hungarian capital, Budapest, were collected. The results of the first analysis by using the Best-Worst Method (BWM) is published in Duleba et al. (2021). Compared to the methodological design and the conclusions of the referred paper, in the current research, two substantial differences can be noticed. Primarily, in this paper, the proposed grey AHP methodology utilizes the whole dataset of the pairwise comparisons on mobility types. Note that in BWM, the pairwise comparisons are reduced to the ones which refer merely to the estimation of importance related to the best and the worst alternatives thus can be considered as a special type of incomplete AHP. However, in the grey AHP process, which is the current proposal, all possible comparisons are considered, and this makes the outcome more robust. Furthermore, as noted in the introduction, the grey AHP is capable of handling the uncertainty of responses, while in Duleba et al. (2021), the authors do not consider the possibility of collecting not correctly estimated crisp numbers in the evaluation of the questionnaires.

The sample is further divided into three groups (i.e., short, mid, and long) of the representative evaluators based on the commuting distance from home to the campus. Those evaluators whose distances are between 0.1 km and 10 km are considered as short-distance commuters, evaluators with 10–40 km are considered as mid-distance commuters, and the evaluators who travel more than 40 km are considered as long-distance commuters. It has to be highlighted that even though the respondents are connected to the university, they are asked to represent their specific commuting group based on their own experience and professional knowledge (Duleba et al, 2021). Thus, the results presented in this section can be considered as a professional consensus about commuting choice supported by own experience. The experts' basic characteristics can be found in Table 3. The gender ratio is balanced, while the age and the educational level are somewhat biased because several young experts, including students, are involved in the study.

Having determined the structure of the mobility types, the scores of the alternatives are obtained with the grey AHP approach. The final scores for each group are aggregated by using the geometric mean technique.

As the initial phase of the analysis, the consistency of the responses is checked by following the AHP method's consistency measure, i.e., the consistency ratio calculation of Saaty (1977), in which the maximum eigenvalue of the pairwise comparison matrices is determined, and a random index is applied. All evaluations perform well, i.e., none of them is over the consistency threshold 0.1; thus, no responses are filtered from the sample. This is a significantly strong argument for the robustness of the created model and the relevance of the survey questions. Moreover, it reflects that the evaluators could provide sufficiently transitive scoring in terms of rating the mobility types.

The first step of obtaining the weight scores and creating the decision matrix is to define the problem and to construct the structure. In this study, six alternatives (i.e., mobility types) are provided as the followings: public transport (PT) (A1), car (A2), car-pooling (A3), walking (A4), bike (A5), and home office (A6). Due to the type of the problem,

Table 3
The respondents' basic characteristics.

Evaluators = 56		%	Nr.	Short-distance	Mid-distance	Long-distance
Total		**100%**	**56**	**24**	**21**	**11**
Gender	Male	44.64%	25	11	9	5
	Female	55.36%	31	13	12	6
Marital status	Married	37.50%	21	8	9	4
	Single	62.50%	35	16	12	7
Age	18–30 years	42.86%	24	12	7	5
	31–50 years	35.71%	20	10	6	4
	greater than 50 years	21.43%	12	2	8	2
Educational level	Primary school	1.79%	1	1	–	–
	Secondary school	1.79%	1	1	–	–
	High school	26.78%	15	7	4	4
	BSc degree	26.78%	15	6	5	4
	MSc/PhD degree	42.86%	24	9	12	3
Working status	Student	26.79%	15	7	5	3
	Researcher	23.21%	13	6	5	2
	Teacher	33.93%	19	9	6	4
	Retired	16.07%	9	2	5	2

there is no criteria defined in the current research. Solely alternatives are compared according to the mobility types (i.e., goal). Thus, basically, it can be stated that mobility types are the only criterion for this problem. Even though in the survey, the drivers of the choice are not evaluated, there are certain reasons behind the selection of the offered alternatives, e.g., the travel time, the cost of traveling, environmental consciousness, and flexibility (Mayo and Taboada, 2020). Besides mentioning the trivial advantages and disadvantages of each mobility type (e.g., the favorable travel time of the car mode, the cost benefit of walking, the environmental consciousness in case of the bike mode, and the flexibility of home office), Car-pooling, one of the most recent modes of commuting, is briefly characterized, as well. The concept is introduced in the frame of sharing economy with the aim of reducing the travel time, the need for parking spaces, and the associated travel expenses by decreasing the number of transiting vehicles in the urban system (Hernández et al., 2018). From an individual point of view, the environmental awareness and less travel costs are the most important advantages, while the organizational effort and time and the reduced comfort and flexibility are the disadvantages (Li et al., 2019).

The next step includes the pairwise comparisons for each node of the structure thus combining them and obtaining the scores by using the calculation procedures given in the methodology section for the grey AHP. The combined pairwise comparison matrix for the alternatives is given in Tables 4, 6, and 8. All pairwise comparisons conducted by the experts are combined by using Equation (5). After combining the pairwise comparisons, Tables 5, 7, and 9 are normalized by using Equations (6)-(8). Afterward, the final priority scores are obtained by calculating the average of the rows of Tables 5, 7, and 9. The grey scores of the alternatives with their rankings are given in Table 10.

All the grey scores and their rankings for the first evaluator group (Group 1), where 24 evaluators who are short-distance commuters (i.e., 0.1–10 km) participate, are combined and listed in Tables 4, 5, and 10.

Table 4
The final integrated grey comparison matrix for mobility types in Group 1.

	PT (A1)	Car (A2)	Car-Pooling (A3)	Walking (A4)	Bike (A5)	Home Office (A6)
A1	[1.0000, 1.0000]	[2.3784, 4.4267]	[7.4448, 9.4574]	[4.4267, 6.4474]	[6.4474, 8.4590]	[4.4267, 6.4474]
A2	[0.2259, 0.4204]	[1.0000, 1.0000]	[6.4474, 8.4590]	[2.3784, 4.4267]	[4.4267, 6.4474]	[2.3784, 4.4267]
A3	[0.1057, 0.1343]	[0.1182, 0.1551]	[1.0000, 1.0000]	[0.1551, 0.2259]	[0.2259, 0.4204]	[0.1551, 0.2259]
A4	[0.1551, 0.2259]	[0.2259, 0.4204]	[4.4267, 6.4474]	[1.0000, 1.0000]	[2.3784, 4.4267]	[1.1892, 2.3784]
A5	[0.1182, 0.1551]	[0.1551, 0.2259]	[2.3784, 4.4267]	[0.2259, 0.4204]	[1.0000, 1.0000]	[0.3536, 0.7071]
A6	[0.1551, 0.2259]	[0.2259, 0.4204]	[4.4267, 6.4474]	[0.4204, 0.8409]	[1.4142, 2.8284]	[1.0000, 1.0000]

After the aggregation of the outcomes in Group 1, the results present that the most-used mobility type is public transport (A1), which is followed by car (A2). Fig. 3 demonstrates the preference position of each transport mode gained by the grey pairwise comparisons of the respondents from Group 1 (i.e., short-distance commuters). Respectively, public transport (A1) is the most preferred mobility type, which is followed by car (A2) and home office (A6), where the high ranking of home office is a bit surprising. On the other hand, car-pooling (A3) is the least preferred mobility type.

All the grey scores and their rankings for the second evaluator group (Group 2), where 21 evaluators who are mid-distance commuters (i.e., 10–40 km) participate, are combined and listed in Tables 6, 7, and 10. Since the possibility of walking (A4) in Group 2 is zero, it is excluded from the list of alternatives.

After aggregating the outcomes for Group 2, the results present that the most-used mobility type is public transport (A1), which is followed by the car mode (A2) similarly to the preferences of the first group. However, in case of Group 2, home office (A6) and car-pooling (A3) are the least preferred mobility types. Fig. 4 demonstrates the preference position of each transport mode gained by the grey pairwise comparisons of the respondents from Group 2 (i.e., mid-distance commuters). Thus, public transport (A1) is the most preferred mobility type, which is followed by car (A2) and bike (A5), while home office (A6) and car-pooling (A3) are the least preferred mobility types.

All the grey scores and their rankings for the third evaluator group (Group 3), where 11 evaluators who are long-distance commuters (i.e., over 40 km) participate, are combined and listed in Tables 8, 9, and 10. Since the possibility of walking (A4) in Group 3 is zero, it is excluded from the list of alternatives.

In case of the third group, the results show that the most-used mobility type is public transport (A1), which is followed by car (A2) and home office (A6). The preference is almost like that of the first and the second groups. Fig. 5 demonstrates the preference position of each transport mode gained by the grey pairwise comparisons of the respondents from Group 3 (i.e., long-distance commuters). As a result, public transport (A1) is the most preferred mobility type, which is followed by the car mode (A2) and home office (A6). On the other hand, the least preferred mobility types are bike (A5) and car-pooling (A3).

The results are similar to that of the previous groups, except for the role of home office. It is visible that from a longer distance, the evaluators prefer the home office solution much more. Interestingly, public transport is the most popular choice even though the distance rises. This clearly shows the evaluators' awareness of the environment and sustainability parameters.

Table 5
The final normalized grey comparison matrix for mobility types in Group 1.

	PT (A1)	Car (A2)	Car-Pooling (A3)	Walking (A4)	Bike (A5)	Home Office (A6)	Crisp Weight*	Ranking*
A1	[0.510, 0.510]	[0.442, 0.823]	[0.239, 0.303]	[0.455, 0.455]	[0.455, 0.455]	[0.455, 0.455]	0.4545	1
A2	[0.115, 0.214]	[0.186, 0.186]	[0.207, 0.271]	[0.242, 0.242]	[0.242, 0.242]	[0.242, 0.242]	0.2418	2
A3	[0.054, 0.069]	[0.022, 0.029]	[0.032, 0.032]	[0.028, 0.028]	[0.028, 0.028]	[0.028, 0.028]	0.0280	6
A4	[0.079, 0.115]	[0.042, 0.078]	[0.142, 0.207]	[0.123, 0.123]	[0.123, 0.123]	[0.123, 0.123]	0.1233	3
A5	[0.060, 0.079]	[0.029, 0.042]	[0.076, 0.142]	[0.056, 0.056]	[0.056, 0.056]	[0.056, 0.056]	0.0562	5
A6	[0.079, 0.115]	[0.042, 0.078]	[0.142, 0.207]	[0.096, 0.096]	[0.096, 0.096]	[0.096, 0.096]	0.0963	4

* The details can be seen in Table 10.

Table 6
The final integrated grey comparison matrix for mobility types in Group 2.

	PT (A1)	Car (A2)	Car-Pooling (A3)	Bike (A5)	Home Office (A6)
A1	[1.0000, 1.0000]	[2.3784, 4.1195]	[3.7224, 5.5663]	[2.6321, 4.4267]	[3.1302, 5.0297]
A2	[0.2427, 0.4204]	[1.0000, 1.0000]	[4.4267, 6.3246]	[2.0000, 3.7224]	[3.1302, 5.0297]
A3	[0.1797, 0.2686]	[0.1581, 0.2259]	[1.0000, 1.0000]	[0.2686, 0.4518]	[0.3195, 0.5946]
A5	[0.2259, 0.3799]	[0.2686, 0.5000]	[2.2134, 3.7224]	[1.0000, 1.0000]	[2.0000, 3.7224]
A6	[0.1988, 0.3195]	[0.1988, 0.3195]	[1.6818, 3.1302]	[0.2686, 0.5000]	[1.0000, 1.0000]

Table 10 shows the comparison of the scoring outcomes of the preferred mode choice for the three commuting groups. The derived scores are from the grey AHP pairwise comparisons; consequently, the lower ranking (i.e., higher score) demonstrates higher preference toward the mobility type. Almost all three groups have the same preferences; however, Table 10 depicts that bike (A5) has the highest score for the mid-distance commuter group, while home office (A6) has higher score for the long-distance group.

For comparison, validation and effectiveness check of the proposed grey AHP application, the results of the fuzzy AHP (Çelikbilek et al., 2016) analyses are provided in Table 11. According to the results in Table 10 and Table 11, there is an exact correlation between them. This correlation as well as having the same ranking with two analyses mean that the grey AHP applications provide correct results under uncertainty in a group decision-making process. In addition, the applications of the grey AHP are easier than that of the fuzzy AHP, and having more correct results with less calculation process is more advantageous while making a decision and carrying out the process in a controlled way. More operations and more complex processes mean an increased probability of having errors and making wrong decisions.

By conducting the AHP method in a grey environment, not solely a ranking of transport mode alternatives can be obtained but a quantified list of the experts' preferences for mobility types, too. Moreover, successfully representing subjective judgements and including the bias caused by personal judgements when minimizing it during the estimation process are part of the current study. Table 11 presents the preference weight scores for the commuting alternatives per group and for the whole sample. Note that for commuting from larger distances, the mode of walking due to its unrealistic situation is not provided. Consequently, for Group 2 and Group 3, five alternatives are granted.

Discussion and conclusions

Based on the results, it can be stated that the proposed model contributes to a more proper understanding of commuter mode choice in the examined case study of Budapest. The decision of analyzing the preferences separately by commuting distance highlights not solely the similarities but the differences in commuting attitudes, as well. In case of all three groups, public transport is the first mobility option followed by private car use, which proves the relative effectiveness of public transport in the inner city and in the suburban areas. Home office gains higher attention for long-distance commuters, while for short and middle distances, it is less preferred. Bike is a relevant option for commuting, but for longer distances, it seems to be not a realistic solution. It is disappointing that car-pooling does not gain the citizens' attention. Thus, more financial resources should be allocated for the promotion of this novel mobility option in the examined city and probably in other cities all over Europe.

Regarding the methodology, mode choice analysis by adopting the grey AHP method can be considered as a pioneer work in the transportation scientific literature. One of the important criticisms about mode choice analysis is that each individual can potentially choose from a different choice set and with different levels, as well. By applying the

Table 7
The final normalized grey comparison matrix for mobility types in Group 2.

	PT (A1)	Car (A2)	Car-Pooling (A3)	Bike (A5)	Home Office (A6)	Crisp Weight*	Rank-ing*
A1	[1.0000, 1.0000]	[2.3784, 4.1195]	[3.7224, 5.5663]	[2.6321, 4.4267]	[3.1302, 5.0297]	0.4311	1
A2	[0.2427, 0.4204]	[1.0000, 1.0000]	[4.4267, 6.3246]	[2.0000, 3.7224]	[3.1302, 5.0297]	0.2720	2
A3	[0.1797, 0.2686]	[0.1581, 0.2259]	[1.0000, 1.0000]	[0.2686, 0.4518]	[0.3195, 0.5946]	0.0571	5
A5	[0.2259, 0.3799]	[0.2686, 0.5000]	[2.2134, 3.7224]	[1.0000, 1.0000]	[2.0000, 3.7224]	0.1504	3
A6	[0.1988, 0.3195]	[0.1988, 0.3195]	[1.6818, 3.1302]	[0.2686, 0.5000]	[1.0000, 1.0000]	0.0895	4

* The details can be seen in Table 10.

Table 8
The final integrated grey comparison matrix for mobility types in Group 3.

	PT (A1)	Car (A2)	Car-Pooling (A3)	Bike (A5)	Home Office (A6)
A1	[1.0000, 1.0000]	[2.6321, 4.4267]	[4.0000, 5.8857]	[3.1302, 4.8990]	[2.8284, 4.6807]
A2	[0.2259, 0.3799]	[1.0000, 1.0000]	[3.7224, 5.5663]	[2.3784, 4.1195]	[3.1302, 5.0297]
A3	[0.1699, 0.2500]	[0.1797, 0.2686]	[1.0000, 1.0000]	[0.3195, 0.5946]	[0.2259, 0.3433]
A5	[0.2041, 0.3195]	[0.2427, 0.4204]	[1.6818, 3.1302]	[1.0000, 1.0000]	[0.2887, 0.5000]
A6	[0.2136, 0.3536]	[0.1988, 0.3195]	[2.9130, 4.4267]	[2.0000, 3.4641]	[1.0000, 1.0000]

Table 9
The final normalized grey comparison matrix for mobility types in Group 3.

	PT (A1)	Car (A2)	Car-Pooling (A3)	Bike (A5)	Home Office (A6)	Crisp Weight*	Ranking*
A1	[0.4858, 0.4858]	[0.4925, 0.8283]	[0.2401, 0.3532]	[0.2733, 0.4278]	[0.2973, 0.4920]	0.4376	1
A2	[0.1098, 0.1846]	[0.1871, 0.1871]	[0.2234, 0.3341]	[0.2077, 0.3597]	[0.3290, 0.5287]	0.2651	2
A3	[0.0825, 0.1215]	[0.0336, 0.0503]	[0.0600, 0.0600]	[0.0279, 0.0519]	[0.0237, 0.0361]	0.0548	5
A5	[0.0992, 0.1552]	[0.0454, 0.0787]	[0.1009, 0.1879]	[0.0873, 0.0873]	[0.0300, 0.0530]	0.0925	4
A6	[0.1038, 0.1718]	[0.0372, 0.0598]	[0.1748, 0.2657]	[0.1750, 0.3020]	[0.1051, 0.1051]	0.1500	3

* The details can be seen in Table 10.

Table 10
The final scores and rankings of the alternatives with the proposed grey AHP.

	The Preferences of the Short-Distance Evaluators (Group 1)			The Preferences of the Mid-Distance Evaluators (Group 2)			The Preferences of the Long-Distance Evaluators (Group 3)		
Ranking	Mode	Grey Weight	Crisp Weight	Mode	Grey Weight	Crisp Weight	Mode	Grey Weight	Crisp Weight
1	A1	[0.3799, 0.5291]	0.4545	A1	[0.3483, 0.5138]	0.4311	A1	[0.3578, 0.5174]	0.4376
2	A2	[0.1902, 0.2933]	0.2418	A2	[0.2156, 0.3283]	0.2720	A2	[0.2114, 0.3188]	0.2651
3	A4	[0.0952, 0.1514]	0.1233	A5	[0.1155, 0.1852]	0.1504	A6	[0.1191, 0.1810]	0.1500
4	A6	[0.0757, 0.1168]	0.0963	A6	[0.0697, 0.1092]	0.0895	A5	[0.0726, 0.1123]	0.0925
5	A5	[0.0442, 0.0682]	0.0562	A3	[0.0471, 0.0671]	0.0571	A3	[0.0456, 0.0639]	0.0548
6	A3	[0.0244, 0.0316]	0.0280	A4	–	–	A4	–	–

* **A1**: Public Transport, **A2**: Car, **A3**: Car-Pooling, **A4**: Walking, **A5**: Bike, **A6**: Home Office

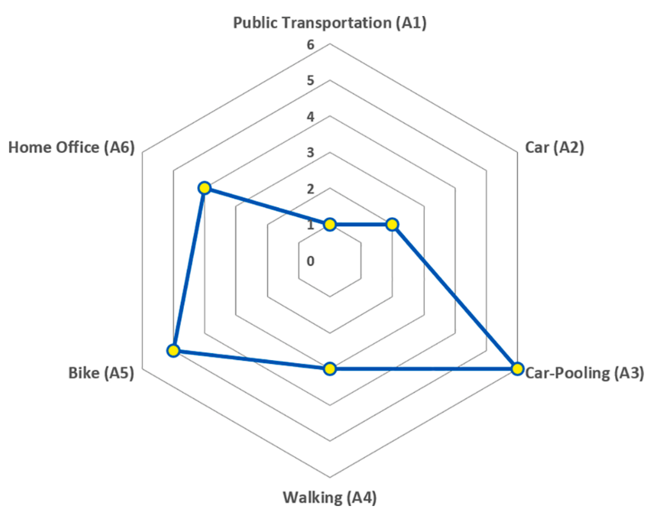

Fig. 3. The gained preferences of the mobility types for Group 1.

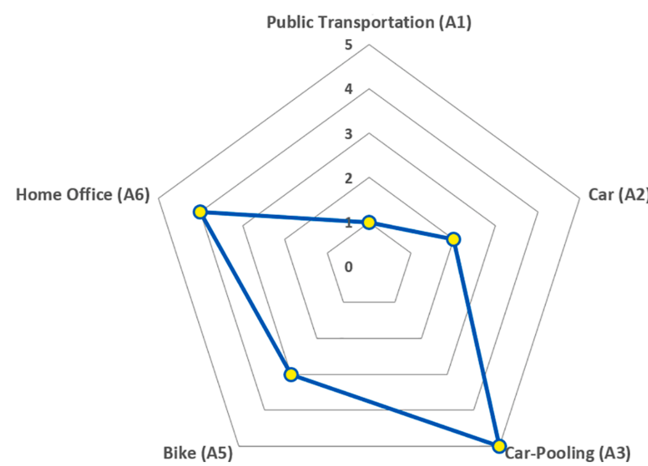

Fig. 4. The gained preferences of the mobility types for Group 2.

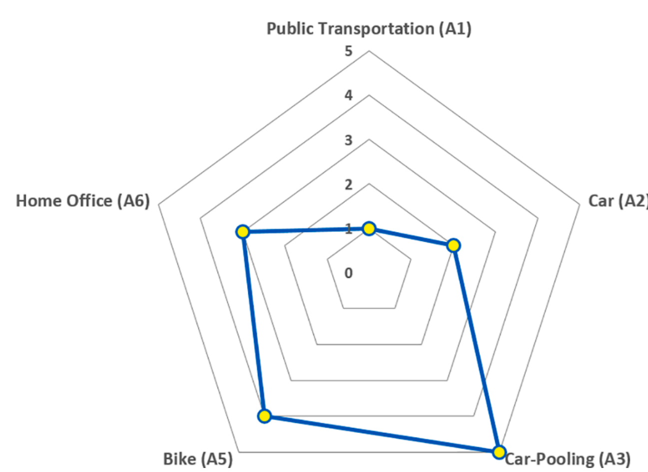

Fig. 5. The gained preferences of the mobility types for Group 3.

AHP method in the grey environment, all of the evaluations done by the experts are applied including the calculations reducing their subjectivities. Therefore, this study and the proposed methodology have promising contributions to the transportation scientific literature. However, considering real-world applications, some benefits and limitations are discovered.

Pairwise comparisons are probably the best tools for mapping the respondents' global attitude toward some alternatives since all relations of the possible alternative pairs are asked and analyzed in the survey process. Moreover, the consistency measure of the AHP method ensures that these relations are logical and transitive to a secured extent due to the application of the consistency ratio threshold. If AHP is integrated with the grey theory, the rigid conventional scoring could be relaxed by considering some neighbor interval values; thus, the derivation of the final weights and the final preference positions of the provided alternatives do not depend to a large extent on the original scoring, which can be biased in some cases.

The hybrid model of the grey AHP in mode choice modeling possesses several benefits, and for the pattern of a certain circle of transportation experts, this methodology can be considered more trustworthy than the conventional MCDM techniques. However, some limitations

Table 11
The final scores and rankings of the alternatives by using the fuzzy AHP for comparison and validation.

	The Preferences of the Short-Distance Evaluators (Group 1)			The preferences of the Mid-Distance Evaluators (Group 2)			The Preferences of the Long-Distance Evaluators (Group 3)		
Ranking	Mode	Fuzzy Weight	Crisp Weight	Mode	Fuzzy Weight	Crisp Weight	Mode	Fuzzy Weight	Crisp Weight
1	A1	(0.733, 0.866, 1.000)	0.8576	A1	(0.539, 0.674, 0.809)	0.6701	A1	(0.557, 0.689, 0.821)	0.6849
2	A2	(0.366, 0.479, 0.591)	0.4797	A2	(0.324, 0.440, 0.556)	0.4414	A2	(0.312, 0.423, 0.535)	0.4249
3	A4	(0.174, 0.240, 0.307)	0.2429	A5	(0.140, 0.215, 0.290)	0.2180	A6	(0.162, 0.231, 0.300)	0.2338
4	A6	(0.134, 0.184, 0.234)	0.1859	A6	(0.051, 0.093, 0.135)	0.0944	A5	(0.059, 0.102, 0.146)	0.1043
5	A5	(0.053, 0.085, 0.118)	0.0868	A3	(0.000, 0.018, 0.037)	0.0193	A3	(0.000, 0.016, 0.033)	0.0171
6	A3	(0.000, 0.007, 0.014)	0.0073	A4	–	–	A4	–	–

* **A1**: Public Transport, **A2**: Car, **A3**: Car-Pooling, **A4**: Walking, **A5**: Bike, **A6**: Home Office

related to the proposed model and survey process are listed, as well.

On the one hand, the drivers of mode choice are not analyzed in this model due to the direct scoring of the alternatives. Consequently, the grey AHP methodology alone might not be appropriate for the modal split predictions because for future trend analysis, understanding the triggers of mode choice are necessary. As a remark for further research, it is noted that the extension of the presented methodology is possible with other MCDM methods for driver analysis (e.g., embedding the hierarchical structure of the drivers is a criterion) or can be combined with different statistics-based methods, for instance with structural equation modeling.

On the other hand, it must be emphasized that the proposed model is inflexible in terms of the offered alternatives. The respondents have no option to amend the list of the offered mobility types, which can be a serious drawback if the pre-selection of these types is not sufficiently thorough. Furthermore, the respondents cannot use a different scale than the one provided, so expressing extreme preference or objection toward certain modes is possible solely to an extent that the scale allows.

Taking all advantages and disadvantages into consideration, the proposed methodology can be recommended to those types of mode choice analysis where some transportation experts are asked to provide the consistent scoring of the determined travel alternatives on the commuting attitude. The final outcomes of the analysis are more trustworthy as well as the survey procedure is simpler and less costly than in other model applications.

Availability of data and materials

The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

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CRediT authorship contribution statement

Szabolcs Duleba: Conceptualization, Validation, Writing – review & editing. **Yakup Çelikbilek:** Methodology, Software, Visualization, Writing – original draft. **Sarbast Moslem:** Formal analysis, Data curation, Writing – original draft. **Domokos Esztergár-Kiss:** Investigation, Resources, Writing – review & editing, Supervision, Project administration, Funding acquisition.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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