Sustainable Cities and Society 74 (2021) 103264

Contents lists available at ScienceDirect

Sustainable Cities and Society

journal homepage: www.elsevier.com/locate/scs

Promoting sustainable mode choice for commuting supported by persuasive strategies

Domokos Esztergár-Kiss *, Yuliia Shulha, Attila Aba, Tamás Tettamanti

Budapest University of Technology and Economics, Faculty of Transportation Engineering and Vehicle Engineering, Műegyetem rkp. 3, Budapest 1111, Hungary

ARTICLE INFO

Keywords:
Mode choice
Sustainable transportation
User preference
Persuasive strategies

ABSTRACT

A personalized route planner is elaborated to support commuting, where soft measures are applied to influence the intentions of individual travel behavior. In order to do that a utility function is created, which consists of four attributes (travel time, travel cost, environmental effect, and health effect) to reflect on user preferences and considers four transport modes (walking, cycling, public transport, and car) as alternatives. The outcome of the utility function is a suggested transport mode based on the attributes, where the travelers may provide a feedback, whether they would really choose the suggested transport mode. During the analysis, statistical methods are used to determine the most substantial factors affecting transport mode choice and trip characteristics. Based on the analysis, travel time is still the most determinant attribute in transport mode choice. Considering the results, the web application suggests in most cases cycling as the best mode choice, and almost half of all users agree to choose the best transport mode, which is suggested by the application. The acceptance rate is much higher in case of public transportation and walking. The applicability of reduction, tunneling, suggestion, personalization, and simulation strategies are demonstrated. The elaborated method supports finding a solution to change travel behavior by understanding the affecting factors of the individual decision-making process, which might help promoting the choice of environmentally friendly transport modes.

1. Introduction

Sustainable travel behavior means that environmental, economic, and social impacts are reduced when users make a travel mode choice, usually different than car, as defined by Sunio and Schmöcker (2017). Sustainable travel behavior is therefore recognized as an essential aspect in the development of socially, environmentally, and economically sustainable communities (Gudmundsson et al., 2016). This can be realized by introducing sustainable urban mobility plans, which focus on those demand management strategies that can facilitate alternatives to private cars (Myrovali et al., 2020). The introduction of such policies might influence the decisions of travelers in cities resulting in a more sustainable travel behavior (Morris & Guerra, 2015). In terms of the negative impact, choosing public transport or active modes (walking and cycling) is considered sustainable compared to car usage (Lind et al., 2015). The promotion of sustainable transportation mode choice mitigates the environmental effects of mobility (e.g. pollution, noise), and has a direct positive effect on the citizens. Therefore, ways of supporting sustainable mode choice need to be further investigated.

The majority of the available strategies aims to influence long-term behavioral change (Andersson et al., 2018; Dastjerdi et al., 2019; Di Dio et al., 2018). Through proper intervention, behavioral change can be triggered, which leads toward the adoption of more sustainable behavioral habits, such as reducing car usage (Anagnostopoulou, Urbancic et al., 2018). Existing strategies consist of soft measures, such as an awareness raising campaign or organizing a bike-to-work day (Martin et al., 2012) and hard measures, such as an establishment of a bike lane or parking regulation (Ferguson, 2016). The main difference between these two types of measures is in case of hard measures the need for infrastructural developments accompanied by higher financial investment requirements, while soft measures usually require lower financial resources are based on information provision. Technologies and soft measures are crucial for sustainable development (Di Dio et al., 2018; Zong & Zhang, 2019). More specifically, information and communication technologies (ICT), more directly Intelligent Transport Systems (ITS), have the potential to influence travel purposes, routes, and mode choice (Iordanopoulos et al., 2018).

This influence can be achieved by persuasive technologies, which are

* Corresponding author.
E-mail address: esztergar@mail.bme.hu (D. Esztergár-Kiss).

https://doi.org/10.1016/j.scs.2021.103264
Received 26 April 2021; Received in revised form 5 August 2021; Accepted 11 August 2021
Available online 13 August 2021

designed to change (travel) behavior of users through influencing individual decisions as defined in Anagnostopoulou, Bothos et al. (2018). Route planning applications (a subset of ICT and ITS) can promote sustainable modes so that these technologies can be used as persuasive techniques to support changes in travel behavior (Giuliano & Hanson, 2017). On the one hand, ICT can change the utility of different transport modes, which has an impact on the transport mode choice by making public transport, walking, and cycling more attractive (e.g. through ICT commuters access the public transport schedules, cycling routes). On the other hand, ICT can represent a barrier to sustainable transport as well, since several mobile applications provide real-time information on traffic and suggest unsustainable modes as the best option. Thus, individuals might be encouraged to drive a car which generates traffic jams in residential areas (Gössling, 2017). Currently, there are several applications developed to nudge users taking into account environmental or health effects (Bothos et al., 2014), but they do not use a combined set of parameters to facilitate behavior change, and do not intend to change the travel behavior of commuters. Therefore, the following research question can be formulated: How to elaborate route planning applications and apply influencing strategies supporting sustainable transport mode choice for the commuters, which could convince people to change travel behavior?

The main added value of the proposed application compared to the existing methodologies (Andersson et al., 2018) is the ability of considering multiple objectives expressed in a comprehensive manner, i.e. the user's utility function for the daily commuting. On the one hand, the present research suggests a selection of strategies to influence commuters' choice towards sustainable options, on the other hand a feasible implementation is proposed and justified via a real-world pilot. Based on previous achievements, the research contribution of this study is to:

- investigate how persuasive strategies can be effectively included in a route-planning application to encourage sustainable travel behavior for commuting,
- create a multiobjective utility function, which considers several parameters to support the suggestion process,
- analyze how specific factors (travel time, travel cost, environmental, and health effect) influence the intention of individual travel behavior in an urban area,
- measure (by direct feedback from the user) whether the traveler preference is accomplished based on the suggestions of the application,
- assess user features, mode choice, feedback, acceptance, and their interconnections.

The paper is structured as the following. Section 2 discusses the related works focusing on mode choice, soft measures, and persuasive technologies. In Section 3, a model is described where a specific utility function is created. Section 4 presents the results, including user related parameters, trip related parameters, and statistical analysis. In Section 5, the results are discussed, and extension options with limitations are mentioned. Finally, Section 6 provides the conclusion of the study.

2. Related works

Mode choice is a complex process which is strongly influenced by different socio-economic and habitual factors. Hilgert et al. (2016) analyze whether and how commuting mode choice patterns vary on the individual level and which factors influence this variation. The results indicate that commuting mode choice is determined by several factors like socio-demographics, commuting tour characteristics, and the availability of cars and transit passes. The study of Li and Zhao (2015) highlights that travelers with higher status tend to travel more by car, while in case of short trips, bicycle is especially popular among the transport modes. De Vos et al. (2016) focus on the relation between mode choice and travel satisfaction, including travel-related attitudes. The researchers find that active travel results in the highest levels of travel satisfaction, and urban commuters evaluate car and public transport trips more negatively than suburban commuters. Based on the results of Hasnine et al. (2018), students tend to choose active modes and public transport when heading to the city center. While considering long-term implications, bike would be much preferred in case of suitable infrastructure. Almarsi and Alraee (2013) develop a mode choice model for work trips. The developed models are able to predict the choice behavior with a high confidence level; however, these models do not aim to change travel behavior nor to suggest transport modes.

The monitoring and understanding of factors influencing transport mode choice is essential in choice modelling since it directly deals with the behavioral aspects of travelers. Generally, the individual mode choice is influenced by factors (Ortuzar & Willumsen, 2011) which can be classified into three categories, i.e. the individual characteristics of the traveler (e.g. income, car ownership, household structure, the possession of driving license, or attitude), the trip characteristics (e.g. trip purpose, the time of the day, or whether it is an individual or group trip), and the characteristics of the transport facility (e.g. travel time, costs, availability, reliability, comfort, safety, and security).

Among the three categories mentioned above the individual characteristics of the traveler is the only one which contains subjective aspects concerning the mode choice for daily commuting, e.g. intentions, attitudes and awareness of consequences are important factors. At the same time, characteristics of the trip and the transport facility are objective parameters, which are given and cannot be influenced. Accordingly, persuasive technique is a promising approach to influence travel behavior towards sustainable travel modes via affecting subjective individual parameters.

Another classification includes five groups of factors (Yang et al., 2018), which are the travel demand determinants, the transport mode characteristics, the socio-demographic characteristics, the subjective attitudes and perceptions, and the environmental characteristics. Other factors (Kwan et al., 2018), which have impact on travel behavior, are the psychological values of the locals, the national economic policies, and changes due to life-course transitions. According to the above, when persuasive techniques are deployed, besides the most influencing factors (travel time and cost), two subjective factors can be taken into consideration, i.e. environmental and health effects.

To provide a suitable utility function for suggesting sustainable transport modes, its parameters must be identified. The results by Almarsi and Alraee (2013) show that the factors significantly affecting mode choice are the total travel time, the total cost, the ownership of the means of transport, the distance, and the age. Sun et al. (2018) consider that in case of car, the influential factors for decision-making are the travel time and the uncertainty of parking. Moreover, it is investigated that under what conditions car users would give up driving and switch to public transport. The study of Ng (2018) illustrates how different policy scenarios might help cities to achieve a more sustainable transportation development, and how important it is to consider carbon emission in model choice models. According to Anagnostopoulou, Bothos et al. (2018), the most commonly visualized information is CO2 emission, cost, and the burnt calories. The scholars assume that in case of a switch to more environmentally friendly transport modes, the cost of mobility is reduced, and users burn more calories. Tajalli and Hajbabaie (2017) study the associations between commuting mode choice and the physical and mental health of travelers in New York City. The results show that walking and using subway are the healthiest modes of commuting. Showing health benefits, when listing the choice options, may have a positive effect on sustainable mode choice. Traditional route planners typically provide only time and distance information, while the health effects of walking or cycling are measured by special apps, which do not intend to change the travel behavior. Thus, these parameters must be considered when constructing a utility function.

The Theory of Planned Behavior was assessed by several researchers.

Olsson et al. (2018) investigated, which parameters have the greatest effect on the reduction on car usage. Using ordered logit models, it was shown that personal norms, attitudes, and perceived behavior control are the most relevant mechanisms that play a role in the mode choice. Klöckner and Blöbaum (2010) elaborated a comprehensive model, where travel behavior changes were investigated using a structural equation model. They found that intentions and habits have a significant impact on the mode choice. Similarly, Sunio et al. (2018) used a stage model of self-regulated behavioral change to analyze the potential behavior changes of university students. The results are based on longitudinal data, using a before and after data collection, where they found that a substantial change in travel behavior can be achieved through four stages: predecision, pre-action, action, and post-action.

Special attention needs to be paid to soft measures in influencing travel behavior. These measures include the promotion of sustainable travel, the educational and travel related awareness campaigns, the advertising campaigns, and the use of travel plans, as stated by Nasrudin et al. (2017). Based on the study of Bamberg et al. (2011), such measures are aimed to influence directly the decision-making process by affecting individual perceptions through the modification of the individuals' judgements on the consequences associated with the use of different transport modes. Bamberg (2013) found that behavior change can be achieved by using personalized information and a stage-based dialog intervention, which resulted in the reduction of car usage.

Andersson et al. (2018) investigate through a theoretical framework, how behavioral change can be reached by implementing smartphone applications. The results suggest that customization, information, feedback, commitment, and good design are important aspects when aiming to encourage the choice of more sustainable modes. Therefore, in this study, these approaches are applied by providing comprehensive information about the transport modes.

Persuasive strategies guide travelers to change their mobility and make sustainable decisions. Some commonly applied persuasive strategies are collected in Table 1. Anagnostopoulou, Bothos et al. (2018) find that self-monitoring, feedback, tailoring, and comparison are the most relevant strategies. According to the research of Sunio and Schmöcker (2017), self-monitoring and feedback are the most used persuasive strategies applied in urban mobility applications.

Bothos et al. (2014) propose a set of persuasive strategies for route-planning mobile applications by using the concept of choice architecture to support travelers to choose more sustainable transport modes. In general, the results show the positive impact of the application on travelers and the change of their attitudes toward environmentally friendly solutions. Anagnostopoulou, Urbancic et al. (2018) aim to change mobility behavior through personalized interventions by using persuasive technologies. A route planner application is developed, and after the pilot period, it is found that 40% of the suggestion, which support more sustainable mode choice, receive positive feedback.

Günther et al. (2020) applied persuasive strategies, such as simulation, gamification, and rewards, to persuade drivers of electric cars to change their driving style. Although in this case the intention was not to change the used transportation mode, but to drive more eco-friendly. They have realized a feedback mechanism combined with financial benefits, but as a result it came out that the gamification elements reached the strongest decrease in terms of energy consumption. Dastjerdi et al. (2019) tested how much individual travel decisions can be influenced using a travel app with persuasive features, where self-monitoring, tailoring, comparison, and gamification were included. They found that enjoyment, social interaction, and the promotion of environmentally friendly options are the main motivation factors. Ahmed et al. (2020) were dealing with personalized travel planning, where they analyzed strategies to achieve behavioral change. They have applied persuasive techniques, where personalization, liking, social learning, and cooperation was applied. Travel plans were created for the users promoting choices of environmental and health benefits. As a result, there was a 25% decrease in terms of CO2 emission and about 6% increase in terms of level of physical activity. Related works are listed in Table 2 summarizing the name of the application, the persuasive

Table 1
Persuasive strategies to change travel behavior (Anagnostopoulou, Bothos et al., 2018).

Strategy	Description
Reduction	Reduces a complex task to a simple activity.
Tunneling	Guides users through a sequence of actions (a step-by-step format).
Tailoring	Provides information according to the needs of the user group.
Suggestion	Provides suggestions to help travelers to reach the target behavior.
Personalization	Provides personalized content/services adapted to specific users.
Self-monitoring	Provides the ability to review the past behavior of the subject.
Simulation	Displays consequences of a particular behavior (links the cause and effect).
Rehearsal	Provides the ability to rehearse behavior or content of the intervention.
Praise	Offers praise in order to make people more open to persuasion.
Reminders	Provides reminders about the target behavior.
Gamification	Implements game elements in a non-game context.
Rewards	Supports target behavior to perform better.
Similarity	A system is designed to look familiar for a user.
Liking	A system with increased visual attractiveness to increase persuasion.
Social role	Acts like it has a social role (e.g. coach, instructor, or buddy).
Social learning	Provides opportunity to observe the behavior of others.
Normative	Influences the target behavior through providing normative information.
Social facilitation	Provides the opportunity to monitor whether there are other users performing the same behavior along with them.
Competition	Stimulates the target behavior through competition with each other.
Recognition	Provides information about the adoption of the target behavior.
Comparison	Provides a possibility to compare the own behavior with others' behavior.
Cooperation	Adaptation of the users' target behavior through cooperation.
Conditioning	Uses principles of reinforcement and shaping to change behavior.
Surveillance	Collection of data about behavior through observation.

Table 2
Web applications using persuasive techniques and their effects.

Name of the application	Persuasive strategy used	Effects, outcomes	Related material
OPTIMUM	all strategies listed in Table 1	through personalized persuasive messages users make more sustainable mobility choices	Anagnostopoulou, Urbancic et al. (2018)
Persuasive Experiment of Chemnitz University of Technology	simulation, gamification, and rewards	drivers of electric cars are persuaded to drive more eco-friendly so that energy consumption can be reduced	Günther et al. (2020)
Advanced Real-time Multimodal Information System for Copenhagen Traffic Management	self-monitoring, tailoring, comparison, and gamification	individual travel decisions are to be influenced using a travel app with persuasive features	Dastjerdi et al. (2019)
SPARROWS	personalization, liking, social learning, and cooperation	through personalized travel planning users choose pro-environmental mobility alternatives	Ahmed et al. (2020)

strategies used, the outcome, and the reference materials.

3. Method

The understanding of travel behavior aids the establishment of sustainable transport systems. This section provides a description of the factors affecting mode choice, the most common approaches used for mode choice analysis (including the suggested utility function), the establishment of the application, the data collection steps, and the applied persuasive strategies.

The first step of the method is to define the parameters, which are the attributes (set by the users) and alternatives (analyzed transport modes), influencing the mode choice. Then, a utility function is created considering the defined parameters. The outcome of the utility function is a suggested transport mode based on the attributes. As a final step, the travelers may provide a feedback, whether they would really choose the suggested transport mode.

3.1. Model description

Discrete choice models (Muro-Rodríguez et al., 2017) are widely applied to determine factors affecting transport mode choice and the probability of choosing a particular mode from various options. These models have the capability to predict individual and group decisions. The individual decision-making process is presented as a sequence of the following steps: the definition of the choice problem, the generation of the alternatives, the evaluation of the attributes for each alternative. According to the study of Ben-Akiva and Bierlaire (1999), a discrete choice model is based on the following general assumptions:

- Decision maker: Defining the decision-making entity and its characteristics. The decision maker is usually assumed to be an individual.
- Alternatives: Determining the available options that an individual considers during a choice process. A discrete choice model includes a finite number of alternatives, which are mutually exclusive and collectively exhaustive. The set of the considered alternatives is called the choice set.
- Attributes: Measuring the benefits and costs of each alternative. A set of attributes forms an alternative. Some attributes may be applied to all alternatives, but some might be more specific.
- Decision rule: Describing the process applied by the decision maker to choose an alternative.

Most discrete choice models are modelled within a microeconomic utility-maximization theoretical framework (e.g. random utility theory). Random utility theory is based on the hypothesis that every individual is a rational decision-maker, maximizing utility related to own choices. The utility of an alternative depends on the attributes of the alternative and the individual that can be observed (e.g. travel cost, gender, and age) as well as on attributes that cannot be observed (e.g. service quality, safety, and convenience) (Cascetta, 2009).

Utility can be defined as a value for an individual. The utility of a transport mode is the attraction associated with a particular transport mode used by the traveler for a trip. It can be stated that an alternative (i) will be preferred and chosen from other alternatives, if and only if the utility of the alternative (i) is greater or equal to the utility of all alternatives (j) in the choice set (Minal & Ravi Sekhar, 2014).

Based on the utility theory, in the algorithm of this study, the alternative with the highest utility value is chosen by the individual. The assumptions of the applied method are the following:

- The individual is a user of the route planning application.
- Alternatives are presented by four modes of transport (m): walking (1), cycling (2), public transport (3), and car (4).
- Four attributes are used: travel time (TT), travel cost (TC), environmental effect (EE), and health effect (HE).
- As a decision rule, the utility function is defined for ranking the transport modes.

There are various forms of utility functions to measure mode choice, which are commonly applied in transport literature and real-world practice, as well (Koppelman, 1981). The utility function proposed in the paper is a linear cost function consisting of four attributes on transport mode choice to reflect user preferences. This function is created to express quantitatively the preference of the individual travelers. During planning routes, the users can specify their own preferences based on their travel habits by using weight parameters *(w)* from 0 (no preference) to 4 (maximum preference) related to the four attributes. Using a Likert scale is a standard process in capturing travelers' viewpoints regarding transport related choice options (Eboli & Mazzulla, 2010). The route planning for the four transport modes is based on Google API, where the cost terms *(C)* are calculated based on the routes provided by Google API. The utility is mathematically represented as a linear function of the parameters of the trip for the specific transport mode *(m),* as described in Eq. (1).

$$u_i = -w^{TT} \cdot s^{TT} \cdot C_m^{TT} - w^{TC} \cdot s^{TC} \cdot C_m^{TC} - w^{EE} \cdot s^{EE} \cdot C_m^{EE} + w^{HE} \cdot s^{HE} \cdot C_m^{HE} \tag{1}$$

where:

- w – weight parameter,
- s – scaling factor,
- C – cost term,
- TT – travel time,
- TC – travel cost,
- EE – environmental effect,
- HE – health effect,
- m – transport mode.

The scaling factor *(s)* is calculated to normalize the terms of the utility function presented in Eq. (2).

$$s^{(attribute)} = \frac{1}{\max\left(C_1^{(attribute)}, C_2^{(attribute)}, C_3^{(attribute)}, C_4^{(attribute)}\right)} \tag{2}$$

Therefore, the elaborated model compares all alternatives based on the results of the route-planning application and suggests the transport mode with the highest utility value.

3.2. Route-planning web application

The developed route-planning web application (https://movecit.codecluster.io) is a pilot action of MoveCit project (INTERREG, 2019). The project ran between 2016 and 2019 and was supported by the INTERREG Central Programme (Fig. 1). The project aimed to address the practical usage and the benefits of sustainable transport modes. The application helps travelers to determine which transport mode is better to use for urban trips (typically for commuting between home and workplace) based on their preferences expressed by the utility function in Eq. (1).

The main steps of the application usage are the following:

- The travelers register and provide information about their general background (age, gender, and education), locations (home and work address), and travel preferences (e.g. car type, biking speed, or the availability of public transport pass).
- The application creates possible routes for each transport mode (walking, cycling, public transport, and car) from the place of departure to the destination with a possibility to add multiple destinations.

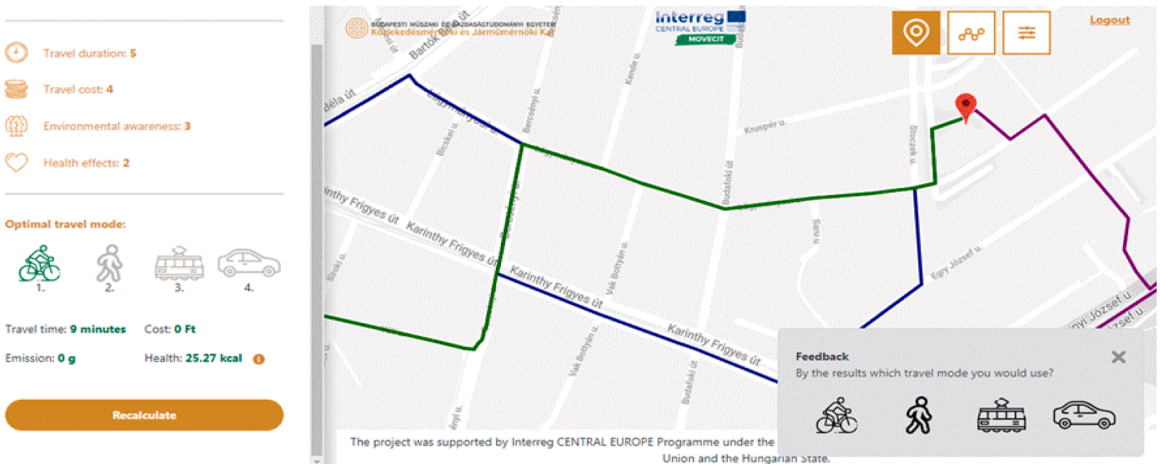

Fig. 1. Example of the planning process in MoveCit web application (https://movecit.codecluster.io).

- The traveler can compare the results of each transport mode based on travel time, travel cost, environmental effect, and health effect. The long-term results related to the weekly, monthly, and yearly periods are illustrated as graphs.
- Finally, the traveler can provide a feedback on the chosen transport mode.

It is worth pointing out that the application does not consider real time data for trip planning (e.g. traffic jams) because it aims to support travel behavior change on a long term rather than providing real time travel information for a specific trip.

Various data are collected from users by the route-planning application. This method of data collection can be considered as stated preference surveying. In terms of the route-planning application, the information is related to actual trips made by the users considering the place of departure, the place of destination, the preferences, and the transport mode they chose from the available alternatives. Basically, the data are gathered through answering a set of questions while creating and setting profiles as well as planning routes in the application. However, users can also plan routes with the application without creating a profile, but in this case the settings and the results are somewhat limited.

The primary data used for the analysis can be divided into two groups.

The first group deals with information related to the profiles of the users, which consists of:

- User characteristics: gender, the year of birth, home, and work address.
- Travel habits and preferences: the most frequently used mode of transport, the usage information of regularly used modes of transport (e.g. average parking time, average cost, or the possession of monthly pass).
- Factors affecting mode choice: weights from 0 to 4 for each transport mode assigned by users, where 0 means the least preferred option, and 4 the most preferred one.

The second group represents data about the trips made by the travelers. The data are collected during the route planning and as an output, displays the information related to each transport mode, such as travel time, distance, emission, health effect, and feedback option. As the main affecting parameters, the following attributes are presented in the application:

- Travel time (min): Travel time includes the duration of the trip and the additional time specified for each transport mode. For example, for trips by car, the walking time to/from the car and search time for a parking place are set.
- Travel cost (Hungarian Forint): The cost of the trip is calculated by the travel distance using data specified by the traveler.
- Environmental effect (g): CO2 emissions are calculated by the average values for public transport and car (e.g. derived from the type and the age of the car).
- Health effect (kcal): It shows burned calories during the trip based on the distance.

The basis of determining the most appropriate transport mode is to use a utility function, which provides a combination of the attributes. Travelers can set priorities (weights) for each attribute by using the scale from 0 to 4 in the application. Even though the most appropriate transport mode based on the profile and the settings of the users is proposed by the application, the traveler may decide not to choose it. The mode choice is a complex task, and it can be influenced by the travelers' psychological factors, attitudes, and personal perception, too. Due to this, each user is asked to leave a feedback on the chosen mode of transport.

The backend is developed in PHP, the database is handled with MySQL, the user interface is developed with Vue.js, while the trip planning is carried out by using Google API via JSON interface. All the data are processed and stored in the centralized database of the route-planning application. The collected data are analyzed by using Matlab software (version R2021a). There are many built-in commands and math functions in Matlab that help users in mathematical and statistical calculations, generating plots, and performing numerical methods.

3.3. Application of persuasive strategies

The route-planning application can be considered as a tool of persuasive strategies. Based on the listed persuasive strategies, reduction, tunneling, suggestion, personalization, and simulation are used in the application (Table 3). The reason for selecting these persuasive strategies is twofold. These strategies are easily usable in a web application. However, the incorporation of more strategies is likely to discourage the participants from using the application.

3.4. Use case of the web application

A typical use case can be described in three steps: getting to know the application (quick planning with modest personalization), detailed planning (every possible personalization), and providing results. These steps are supported by the following three main pages of the application.

The landing page (Fig. 2 **Error! Reference source not found.**) has a

Table 3
Persuasive strategies used in the application.

Strategy	Description
Reduction	It reduces a complex task to a simple activity. The mode choice is a complex decision with several parameters, which is reduced by using four main attributes and by providing a ranking of transport modes based on personal preferences applying the utility function.
Tunneling	The users are guided towards their choices; the uncertainty is reduced because they are able to plan their trips step-by-step. The application provides detailed settings to determine the individual travel behavior characteristics, and during the planning, only the weights have to be set, the ranking and suggestions are automatically generated.
Suggestion	The transport mode which is proposed to the user based on the personal preferences is highlighted. The application provides a ranking of the transport modes by using the weights and the parameters which are set by the traveler during the planning and in the personal settings.
Persona-lization	The application offers personalized content which helps to reach better results. Specific transport related parameters can be set by the user, such as car type, biking speed, or the availability of a public transport pass. With the parameters and the weights assigned to the transport modes, a fully personalized mode choice recommendation is created by the application.
Simulation	The developed application informs the users about the possible consequences of choosing a particular transport mode. Not only the ranking of transport modes is shown, but the travel time, the travel cost, the environmental effects, and the health effect of the different mode choice are provided to the traveler, too. Thus, with all available information the traveler can make a more conscious decision, which is reflected in the feedback.

registration-free quick planner for those, who do not want to register, but have some initial interest in the application. The blue area serves for setting the origin and the destination, and the selection of the departure time. The orange area contains the sliders for the attributes (travel time, travel cost, environmental effect, and health effect), but it is not active for unregistered users. The map view in the yellow area provides the route visualizations.

When a user chooses to register, more complex functionalities can be reached, where the settings can be also stored. In the Registration page (Fig. 3) in blue area the home and workplace address can be stored, while in the orange area the parameters can be changed. The red area is to collect information about age, gender, and education. The green area contains a mode-specific list with detailed parametrization possibilities, such as the walking time to the first public transport stop or the average cost of private car usage. The parameters have a default value, which can be modified by the users based on their experience.

On the results page (Fig. 4) the chosen settings are shown, where the blue area represents the origin and destination, and the orange area represents the attributes. The green area provides the numerical results and the suggested transport modes in order based on the utility function, whereas the yellow area served to show the route results on the map, highlighting the selected routes from each transport mode. Finally, the purple area shows the feedback option.

3.5. Sample description

Considering the trips (Table 4), more than half are created by male

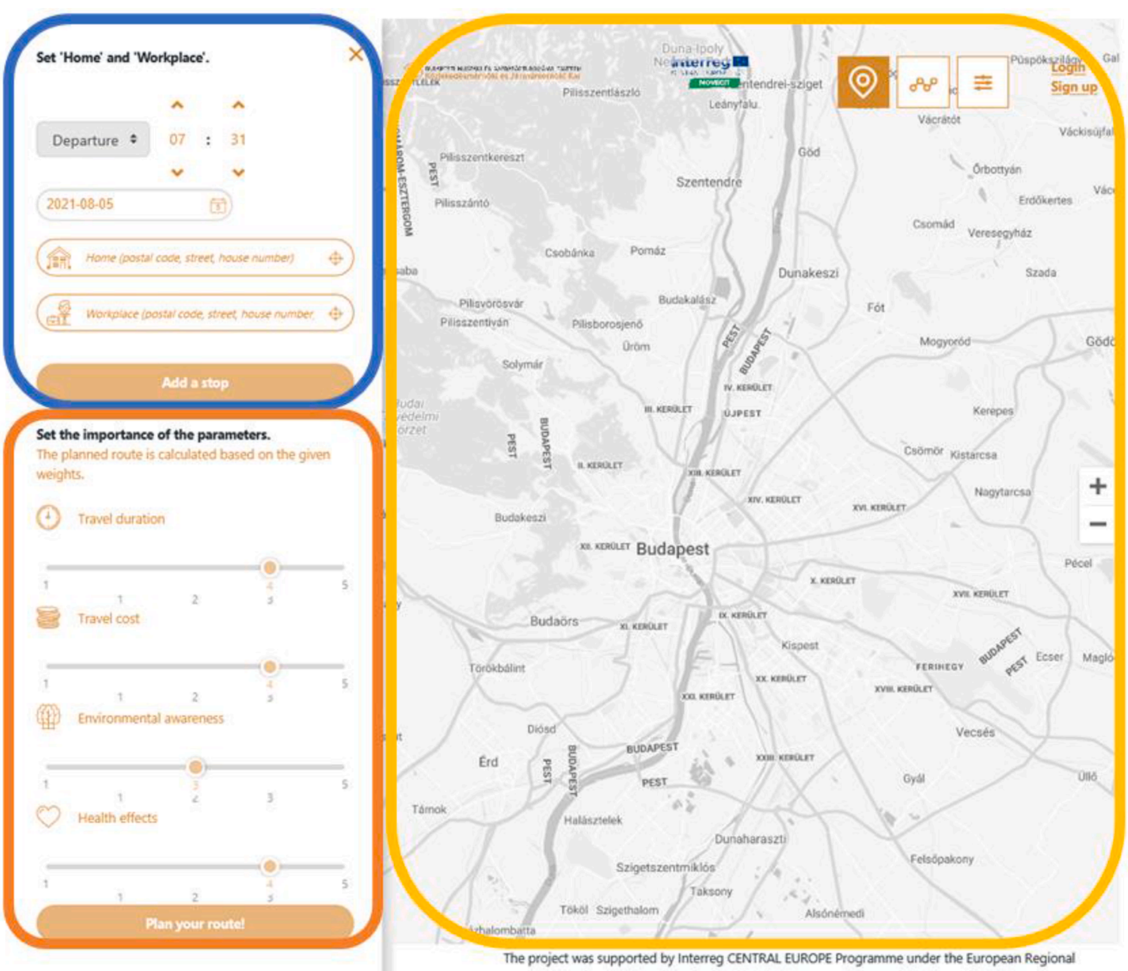

Fig. 2. The landing page of the web application.

Fig. 3. The registration page of the web application.

users (56%), and about one third are created by female users (31%), while 13% of the users do not specify the gender. Regarding the age, younger and older generations are defined reflecting the Hungarian demographic feature, i.e. people under 26 years old are more likely to be still university students than workers. In this vein, more users are coming from the younger generation (57%) and less from the older generation (43%). The mean value of age is 29 with a standard deviation of 6.6, where the minimum age is 20 and the maximum age is 64. In terms of car ownership, 31% of the users own a car, and 69% do not own a car, which is close to the country's average values (regarding car ownership by families). Considering public transportation (PT), users with a monthly pass (81%) are well represented. In terms of education users with university diploma are overrepresented with 58%. The generally used transport modes for commuting are also assessed, where more options could be chosen as travel preferences. In most cases public transport is combined with another transport mode, such as walking (67%), car (53%), and cycling (47%). The bias in the gender and age is caused by the fact that the application was highly promoted among university students of engineering. However, the general analysis clearly shows that not only students used the application; thus, the data set

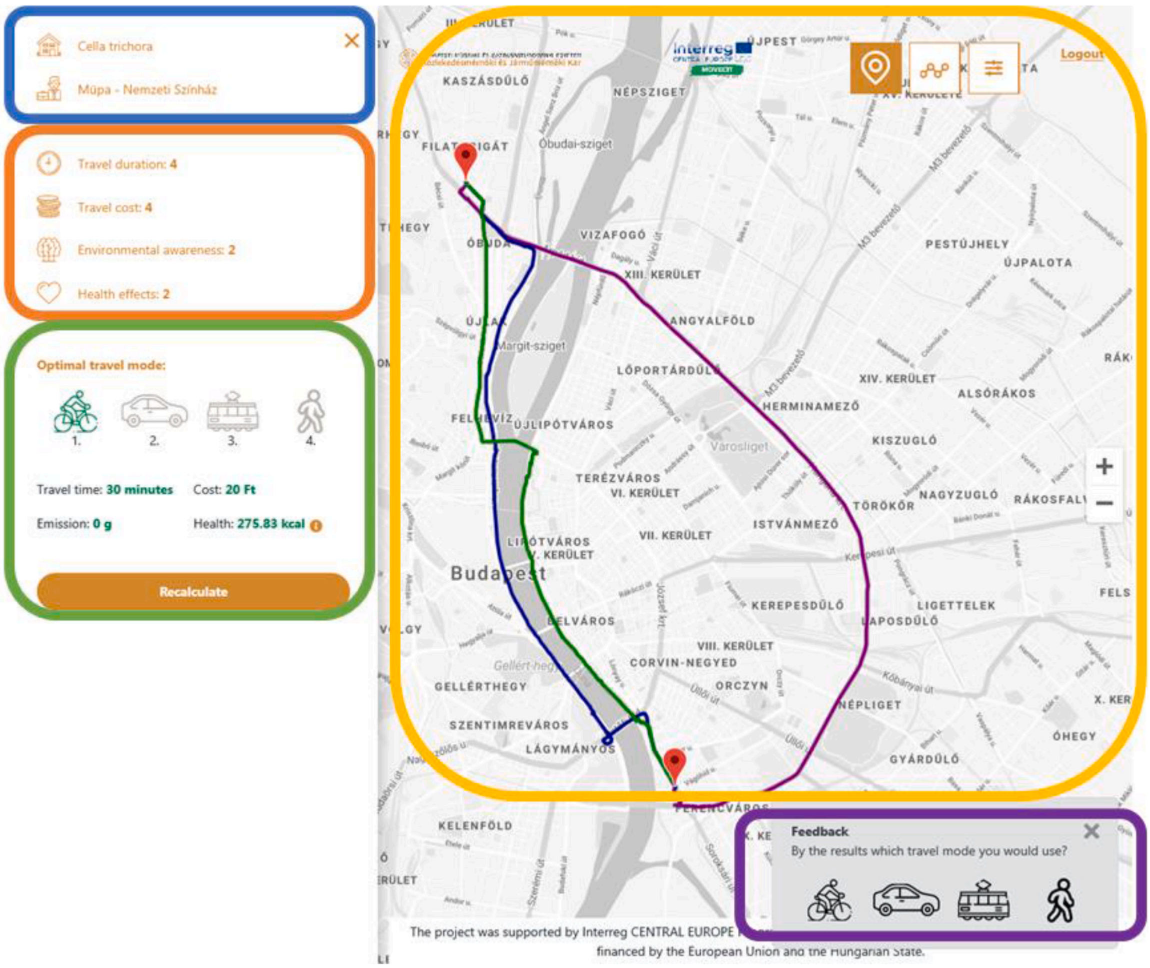

Fig. 4. The results page of the application.

Table 4
General analysis of the users participated in the data.

Parameters	Options	Percentage
Gender	Male	56%
	Female	31%
	Not specified	13%
Age	Younger users (<=26 years)	57%
	Older users (>26 years)	43%
Car ownership	Yes	31%
	No	69%
PT pass ownership	Yes	81%
	No	19%
Education	Elementary school	1%
	High school	41%
	University/College	58%
Travel preferences	Car and public transport	53%
	Cycling and public transport	47%
	Walking and public transport	67%

might be relevant in conducting further analysis.

4. Results

The application was tested in Budapest from November 2018 to November 2019. The route planner was advertised among the university community via social media channels and through e-mail lists of specific user groups. During this period, 400 valid trips were generated by the web application and the number of the created individual profiles achieved 161. In the raw database, the total number of trips reached more than 1000, but in order to avoid redundancy, those trips were filtered out which appeared multiple times with the same settings originating from the same user. Thus, two types of data are used for the analysis: information about the users, such as age, gender, and travel related preferences as well as information about the planned trips, including mode choice, feedback, and acceptance. Reduction, tunneling, suggestion, personalization, and simulation persuasive strategies are demonstrated by the results of the pilot, and are incorporated directly via the functionalities of the application.

4.1. Attributes

In order to analyze the importance of the attributes which influence transport mode choice, the average weights of the attributes (Table 5) and the distribution of the values are calculated (Fig. 5). After registration, the users set the weights from 0 to 4 for their trips based on the attributes used in the application. The most determinant attribute of transport mode choice is travel time with an average of 2.75. This highlights that users consider travel time as lost time, which consequently, should be minimized. Although travel cost (1.81) is the second most important attribute, the difference between this attribute and the

Table 5
Average weights of the attributes.

Attribute	Travel time	Travel cost	Env. effect	Health effect
Average weight	2.75	1.81	1.79	1.09
Standard deviation	0,82427	1,015372	0,838624	1,102304

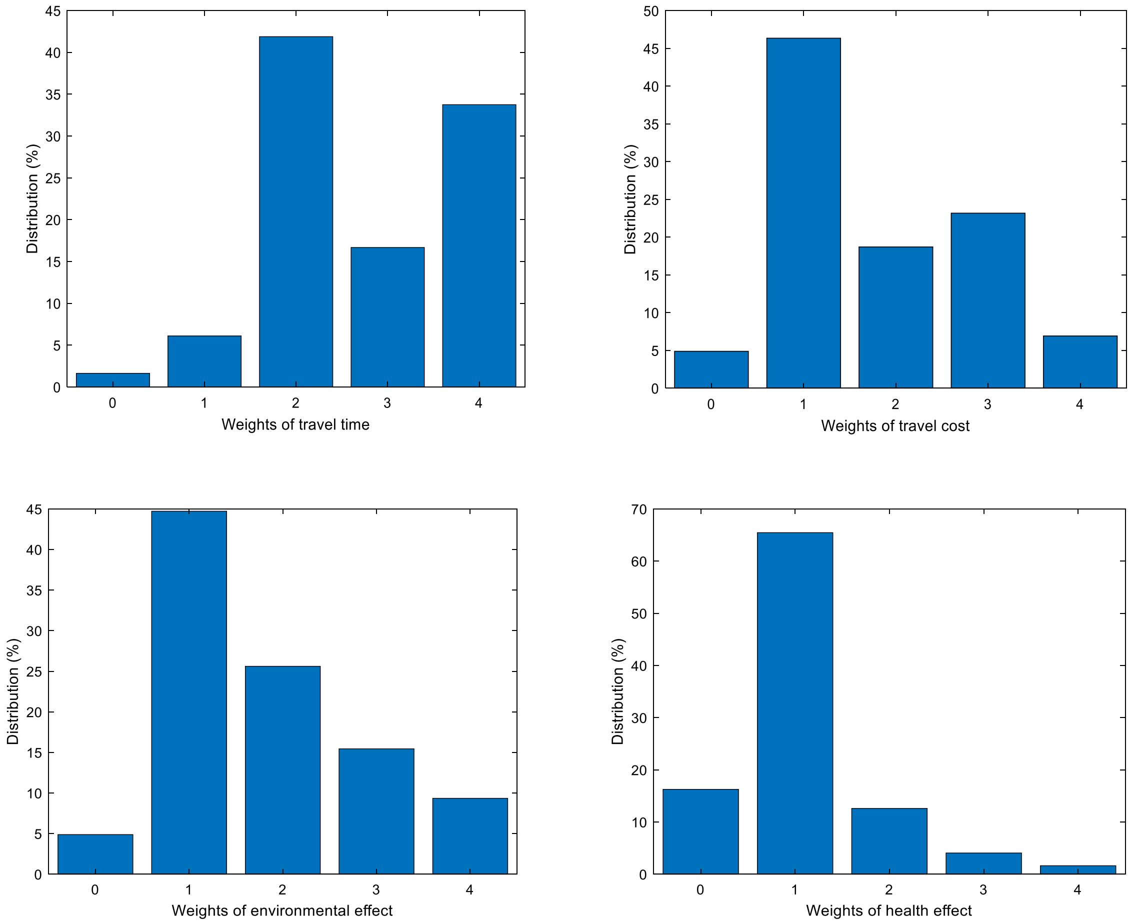

Fig. 5. Distribution of attribute weights.

third one, the environmental effects (1.79) is negligible. Thus, it can be concluded that during their mode choice decisions, users consider the environmental impact of traveling in an increasing manner. The result confirms the intention of the project's goals, i.e., people must be encouraged to use environment-friendly transport modes. Although the attribute of health effect is the lowest in average (1.09), it is still remarkable considering that the full scale is from 0 to 4. It suggests that people are aware of their health during travel, in a measure of more than 25% in general.

By analyzing the distribution of the attribute weights (only discrete values are allowed), it can be concluded that travel time has the most choices of value 2, which is followed by value 4. Obviously, the most weights with value 4 are present (35%) in case of travel time, that is why this attribute is the most important.

In case of travel cost, most of the choices are value 1, which is quite surprising, i.e., 50% of the users (including value 1 and value 0) do not consider cost as a decisive factor. This result presents an important fact that money is not the sole tool to influence travel behavior as it is frequently considered by policy makers (Bhatt et al., 2008).

The environmental effect has similar level of choices of value 1, which means that 50% of the users (including value 1 and value 0) do not think that emission is important for them. However, in this case almost 10% of the users consider this as the most important aspect (giving value 4).

The health effect is much less appreciated, as almost 80% of the users do not consider this attribute as an important one. Note that this result does not indicate that people do not care about heath. It rather shows that nowadays, people do not think about travel time as a useful time to serve health related purposes.

Altogether, except for health effects, less than 5% of the users consider any of the attributes as absolutely not important (giving value 0), but at the same time, except for travel time, similarly less than 10% of the users consider the other attributes as absolutely important (giving value 4).

Using the attributes, the reduction strategy is applied, which practically makes the modeling of the complex decision with a few parameters possible. Leaving the opportunity to the users to set these parameters and applying the utility function to model the transport mode choice, a transparent procedure is provided to support user decision.

4.2. *Travel time and travel distance*

Travel time and travel distance are important parameters affecting mode choice. For each trip, the best mode is suggested by the application, which might be car, public transport, cycling, or walking. The

Table 6
Mean and standard deviation of travel distances and travel times.

Transport mode	Mean (min, max) travel distance (km)	Std. dev. of distance (km)	Mean (min, max) travel time (min)	Std. dev. of time (min)
Walking	1.28 (0.29, 5.65)	1.39	14.42 (3.48, 71.50)	17.78
Cycling	7.35 (0.57, 28.6)	5.21	29.28 (2.00, 107.01)	18.52
Public transport	26.84 (1.53,86.31)	22.53	49.44 (5.82, 109.02)	27.24
Car	31.73 (15.2,61.85)	18.13	41.96 (31.16, 54.90)	10.23

mean and standard deviation of the travel distances and travel times are calculated for the best transport modes (offered by the application), see Table 6.

Walking has a mean travel distance of 1.28 km, which is quite normal, as people do not usually walk too far to reach their workplaces. Cycling has a mean value of 7.35 km, which means that this mode is suggested mainly for shorter trips. In case of public transport, the range (26.84 km) is similar to that of the car (31.73 km), which means that longer trips, especially from the agglomeration are suggested by these modes. It should be noted that travelers could also plan trips from the agglomeration; thus, the average values are higher than urban averages. In terms of standard deviation, the car's is relatively low, but this is due to the low number of proposed suggestions by car.

Considering the travel time, walking (14.42 minutes) is followed by cycling (29.28 minutes), which means that on average trips more than 30 minutes are not suggested by these modes. The average travel time by car (41.96 minutes) is less than the average by public transport (49.44 minutes), which means that commuting by public transport takes a bit longer.

From the histograms in Fig. 6, it can be derived that the usual travel distances are up to 15 km, and usual travel times reach from 10 minutes to 50 minutes.

Furthermore, the distribution of travel distances and travel times is analyzed, as well. In Fig. 7, it can be observed that in case of walking, every suggested trip is within 10 km and in case of cycling, within 30 km. Commuting by car and public transport are very diverse, up to 90 km. Considering the travel times, walking is usually up to 20 minutes, but in some cases, it can be even more than one hour. Cycling is mostly suggested for trips lasting less than one hour. Public transport covers almost all-time intervals; however, usually, it is not suggested for trips lasting less than 10 minutes. This result confirms that the suggestions of the application are correct and effective for practical use.

4.3. Transport mode choice

As one of the main features of the application, based on the results of the utility function, the transport modes have an order, and there is a best choice among them relying on the parameters set by the users (Fig. 8). In most cases, cycling is ranked as a first choice (77%). This is mostly caused by the fact that travelers set relatively high weight on travel time, travel cost, and environmental effects, and bike is a very efficient transport mode considering these parameters. Public transport reaches 17%, while walking and car are practically not suggested as a best mode to travel. This can be mainly because in the case of car, all costs have been incorporated, and a very realistic travel time, including parking time is calculated, which puts this mode in a disadvantageous situation.

The suggestion strategy is realized by providing the best transport mode. Based on the results, usually sustainable transport modes are suggested, which is completely in line with the general aim of the application.

By analyzing the registered users' gender and age, it can be stated that the gender distribution of the best mode choice suggestion by the application (male: 55-62%, female 32-37%) is very similar to the gender distribution of the sample (male 56%, female 31%) in all cases of transport modes (Fig. 9). Only car is an exception since it is suggested only for male registered users (but this is due to the car ownership and the possession of driving license rather than the gender). This means that there is no specific gender-based difference between the suggested trips by the application.

Considering age, only walking suggestion (younger 60%, older 40%) correlates with the age distribution of the sample (younger 57%, older 43%). However, cycling and public transport are suggested more often for the older generation. This is well understandable in case of public transport, and it provides a positive encouragement to older generation to utilize bike more often as a transport mode.

4.4. Feedback and acceptance

Feedback is a response of a user to the proposed transport mode for each trip. At the end of the process, after the application calculates the best modes (based on the inputs and the preferences of the users), the traveler is asked to accept or reject the calculated best mode choice. If the suggested mode is not accepted, the users give feedback on their own choices.

From the 400 trips generated, the users left a total of 156 feedback information. Considering those users who created a profile, the proportion of providing feedback is much higher (48%) than in case of users who did not create a profile, where this value is only 25%.

This justifies that tunneling strategy works. Thus, if users are willing to create a profile and provide information about their intentions of travel behavior, their planning related uncertainty is reduced because of the step-by-step approach, and they are more likely to give feedback on their choices, too.

Considering the feedback, 42% of all users agree to choose the best transport mode, which is suggested by the application. When gender and age are considered (Fig. 10), it becomes evident that male travelers are more willing to accept (46%) the suggestions than female users (32%), while age has not a significant effect on that.

It is emphasized that the suggested order of the mode choice is effective, too, i.e. it is still a positive result considering the general aim of sustainability, if the user chooses the second option instead of the best suggested mode. Taking into account the first- and second-best mode choices, the acceptance value increases from 42% to 87%, which truly

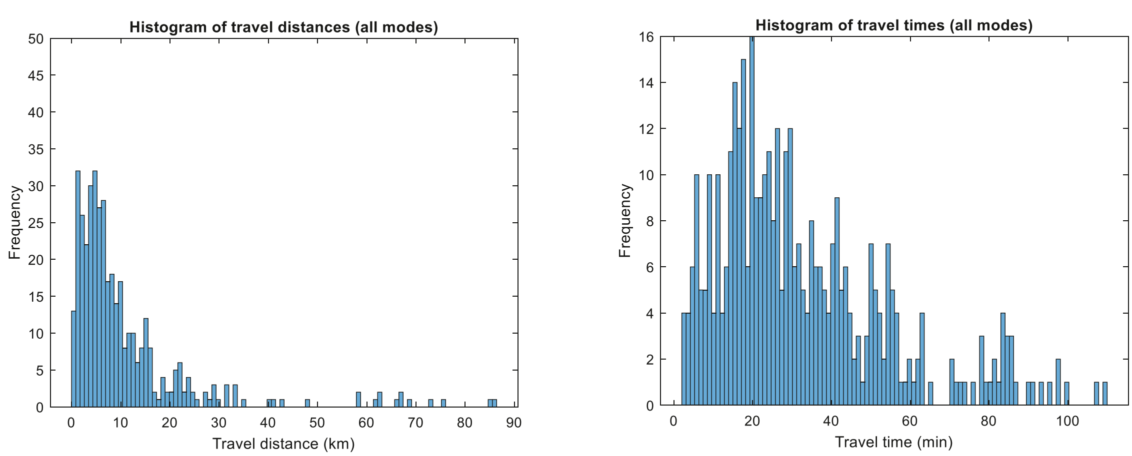

Fig. 6. Histogram of travel distances and travel times.

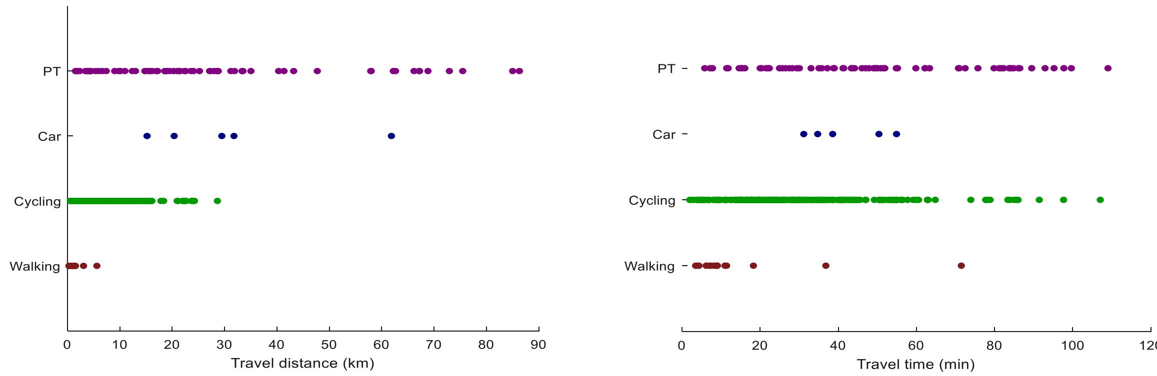

Fig. 7. Distribution of travel distances and travel times.

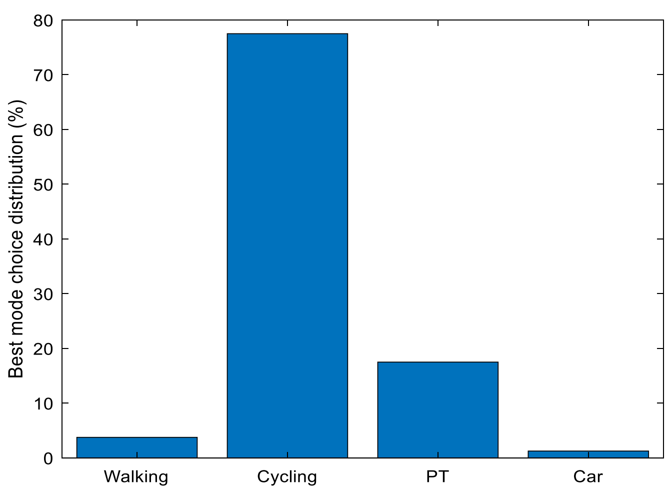

Fig. 8. Distribution of best transport mode choice suggested based on the utility function.

justifies the usability of suggestions provided by the application.

Thus, the personalization strategy is a success, too as a personalized content is provided to those users who registered. Furthermore, it is likely that travelers accept the personalized suggestions proposed by the application.

In order to model the acceptance of the application's suggestion, multivariate logistic regression was applied to the data with binary output (Long, 1997). This is a regression type, where one or more independent variables (predictors) are analyzed according to the observed outcome, which can take only two possible values (0 or 1). The chosen predictors were the age of the users and the distance between home and workplace/school. The output was the decision of the user, i.e. accepting (1) or not accepting (0) the suggestion. The logistic function to be modeled is as follows:

$$p(x) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 x_1 + \beta_2 x_2)}} \tag{3}$$

where:

- p is the probability of accepting the suggested transport mode by the application,
- x_1 and x_2 are the predictors, i.e. the age of the users and the distance between home and destination,
- β_0, β_1 and β_2 are regression parameters.

The results of the multivariate binomial logistic regression are shown on Figs. 11 and 12 filtered by the suggested transport mode for public transport and cycling. For this analysis only a subset of the measured data could be applied, i.e. users who provided feedback after using the pilot web application. That is why the regression was not applicable for private car and walking modes due to the very small number of data (less than 10 samples for these modes).

It is observable that the distance between home and workplace/school location is a highly determinant independent variable for the persuasion. Besides, the age of the users also counts, i.e. the older is the user, the more likely will be the nudge accepted. Table 7 summarizes the coefficients (β, p) of the multivariate logistic regression with the related p-values for public transport and cycling.

4.5. Feedback and transport mode choice

When the transport modes are separately handled (Fig. 13), it can be observed that the acceptance is much higher in case of public

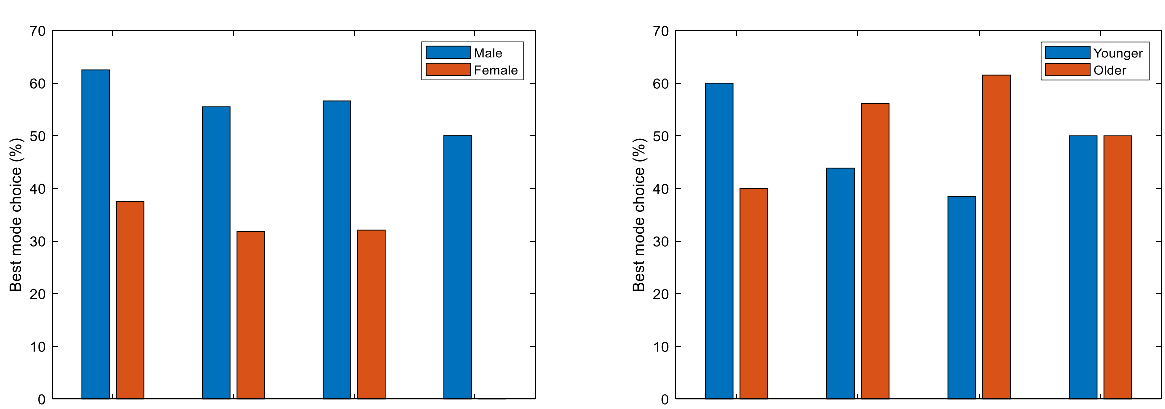

Fig. 9. Best transport mode choice per gender and age.

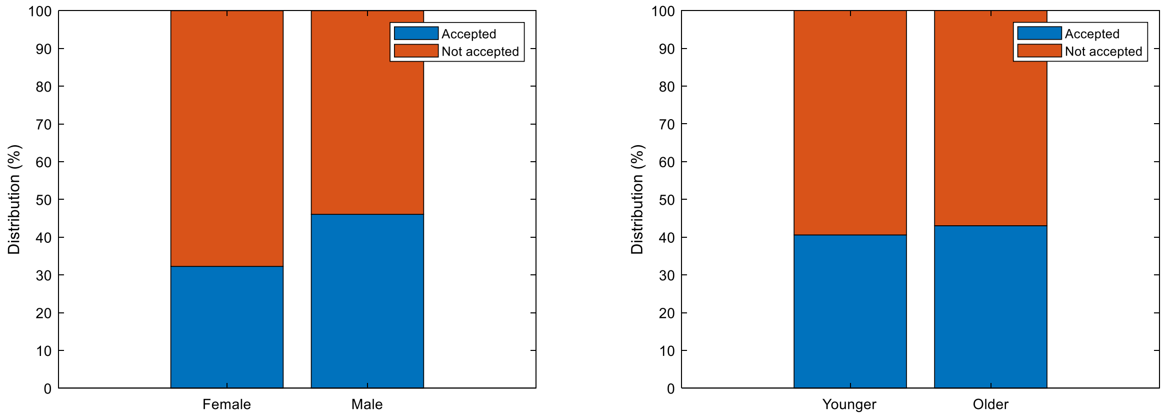

Fig. 10. Acceptance rate of the best mode choice per gender and age.

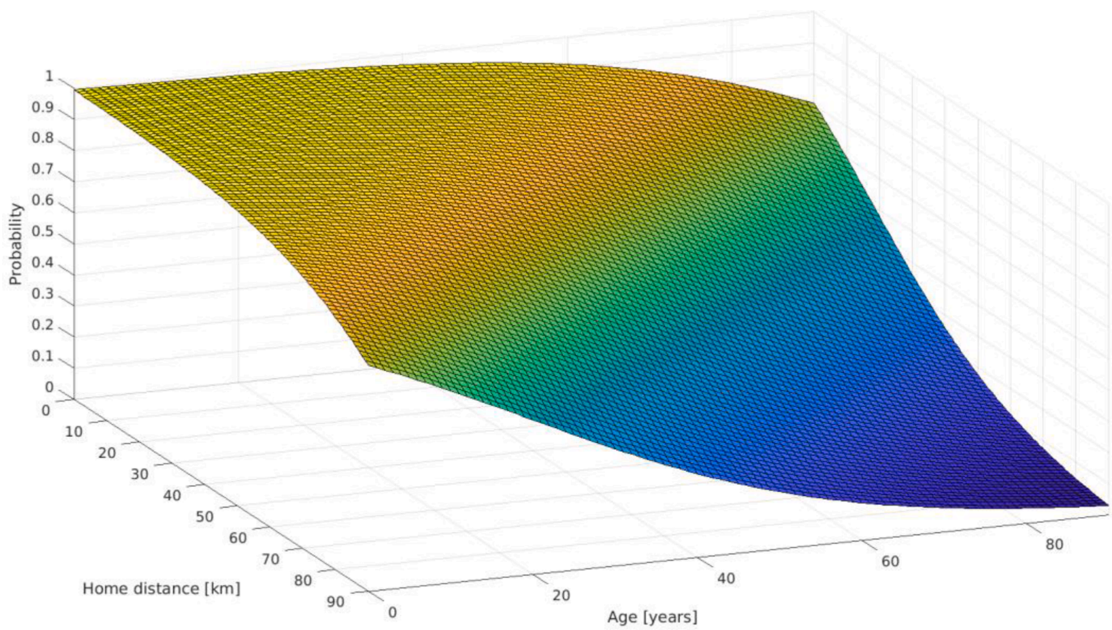

Fig. 11. Probability of user acceptance for public transport as a suggested mode considering age and distance.

transportation (87%) and walking (75%) than traveling by car (50%) or cycling (28%). The very low number of users willing to choose the bike is because of the lack of a well-established cycling infrastructure in the city. Furthermore, the fact that cycling is suggested significantly more often than other transport modes, creates this specific situation where not all travelers tend to choose the best transport mode based purely on the parameters.

As Fig. 13 analyzes the acceptance rate of each transport mode, but it does not provide information about the modal share of the travelers, this aspect is put into focus, as well. Most of those users who provide feedback and accept the best mode choice use bike (50%) and public transport (40%), while those who do not accept, are mostly bikers.

The relation is examined between the set attributes and the feedback provided by the users (Fig. 14). Those registered users are included in this part of the study who consider the attribute levels important (level 3 or 4) and provide a feedback on their mode choice (walking, cycling, public transport, or car). Based on the Budapest pilot data, it is observable that the users considering travel time and travel cost as an important influencing factor primarily choose public transportation (67%). Furthermore, public transportation is mostly chosen by users who care about environmental factors when choosing the transport mode. However, among these users, cycling is chosen by 1/4 of the users, too. Interesting results are provided in case of health effects, where users rather walk or use bike, when they consider this attribute important.

Bike users and walkers do not consider travel time and travel cost so much as decisive factors (less than 20%). While travelers choosing car usually do not consider travel cost and health as an important attribute.

Finally, to support the conscious decision of the users, the long-term impacts of each transport mode choice are visualized in terms of the four attributes (travel time, travel cost, environmental effect, and health effect), which can be seen in a weekly/monthly/yearly period. In Fig. 15, which is a screenshot from the web application, the result of a typical trip is shown by the application considering the environmental effect (i. e. the CO2 emission in g), which is the highest in case of car and the lowest in case of walking and cycling.

This analysis confirms the applicability of the simulation strategy, where the users are informed about several aspects of their transport mode choice, and they have the opportunity to choose and to provide feedback on their decisions.

5. Discussion

Based on the analysis, travel time is still the most determinant

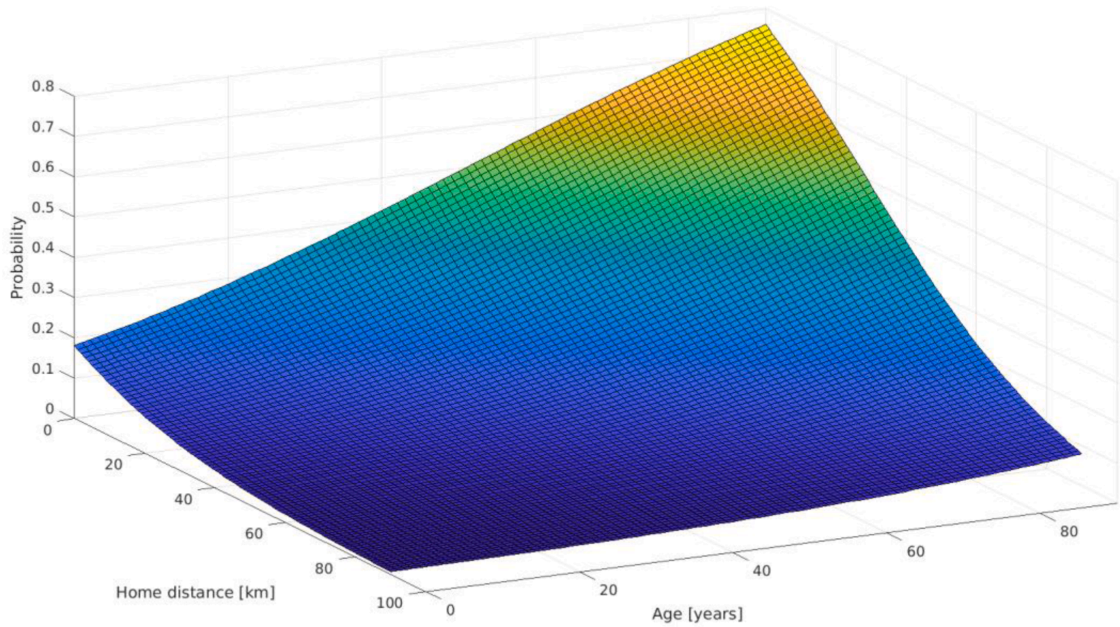

Fig. 12. Probability of user acceptance for cycling as a suggested mode considering age and distance.

Table 7
The coefficients of the multivariate logistic regression concerning the user acceptance for public transport and cycling.

Transport modes	β	p
Public transport	[-5.3114 0.0483 0.0492]	[0.1108 0.1466 0.6078]
Cycling	[1.5081 0.0398 -0.0295]	[0.0624 0.3209 0.2378]

attribute in transport mode choice. Considering the results, the web application suggests in most cases cycling as the best mode choice, and almost half of all users agree to choose the best transport mode, which is suggested by the application. The acceptance rate is much higher in case of public transportation and walking. The elaborated method supports finding a solution to change travel behavior by understanding the affecting factors of the individual decision-making process, which might help promoting the choice of environmentally friendly transport modes.

In order to find effective solutions related to excessive car use, changes in travel behavior are required. In general, the choice of a particular transport mode is influenced by a variety of factors. Therefore, it is crucial to understand the affecting factors and the individual decision-making process. This understanding might help transport planners and policy makers to take measures for mitigating the negative effects of urban transportation by promoting the choice of environmentally friendly transport modes which might bring changes in the travel behavior of travelers.

Before registration, data handling information was available for the

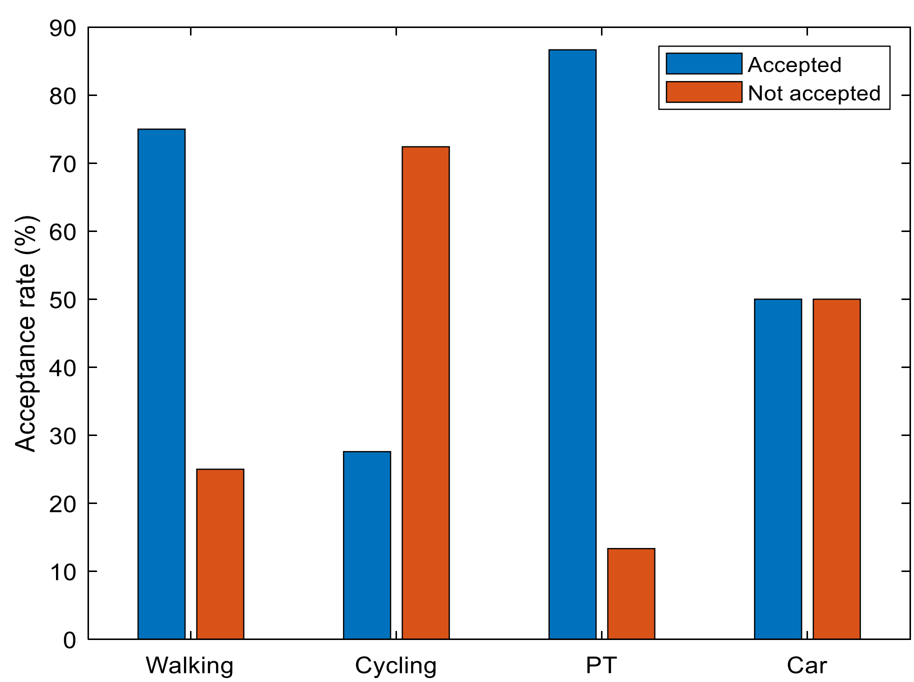

Fig. 13. Acceptance rate of best choice per transport mode.

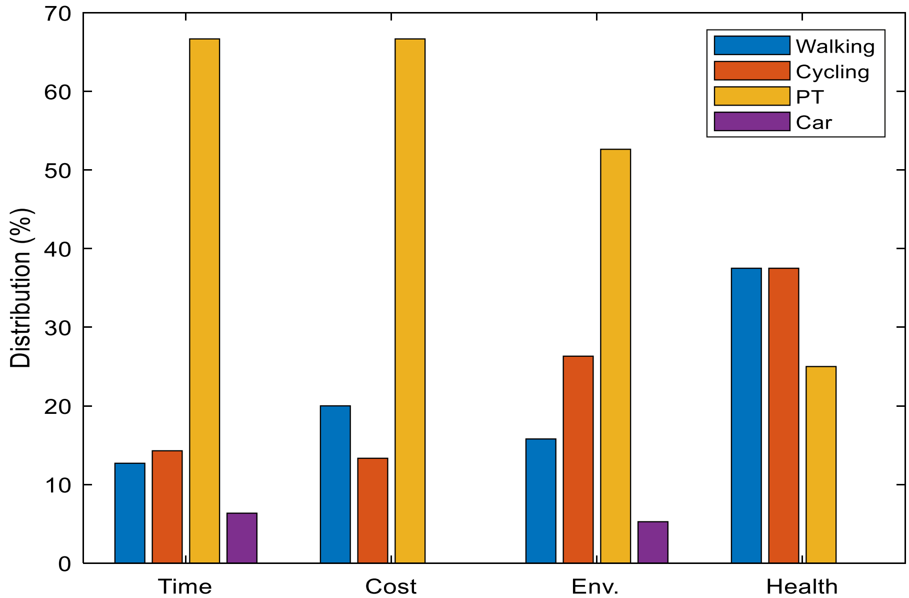

Fig. 14. Distribution of the mode choice per attributes among users who set the attribute levels 3 or 4 and provided a feedback on their mode choice.

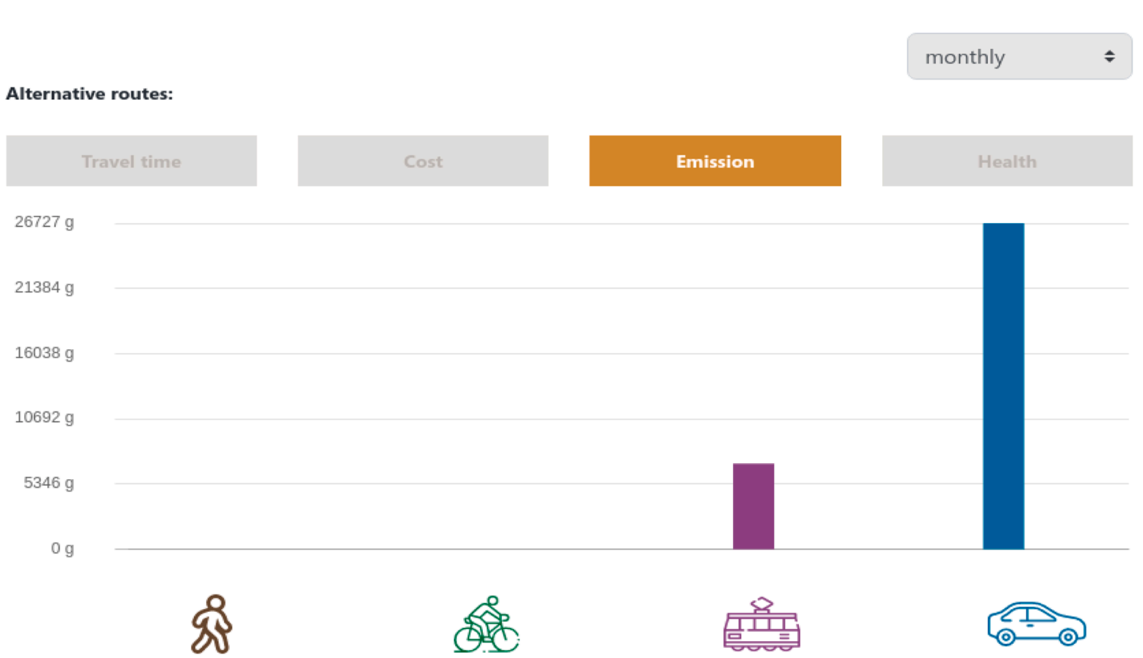

Fig. 15. Long term impacts of transport mode choice showing the monthly CO2 emission (g).

users, where they could be informed about the data handler, the aims of data collection, the types of handled data, the duration of data handling, and the data processing methods. The data protection was ensured by following the General Data Protection Regulation (GDPR) rules, and the users could ask anytime to delete their data from the database.

Based on the analysis of the importance of the attributes which affect travel behavior, it is determined that travel time has still the highest average value in transport mode choice. Meanwhile, the environmental and health effects play less relevant roles. Therefore, it is suggested to launch an educational campaign to increase the awareness of travelers about the negative impacts of unsustainable mode choice on the environment and highlight the importance of a healthy lifestyle.

The travelers provided a feedback reflecting on their intentions, but as commuting is strongly influenced by habits, it cannot be assured that their travel behavior changes. This change should be supported by other actions, such as awareness raising campaigns, innovative measures, and financial incentives to reach that travelers decide on a sustainable mode choice on a long term. The results of the pilot, where 42% of the users agreed to follow the best transport mode suggestion are similar to the results provided by Anagnostopoulou, Urbancic et al. (2018), where 40% of the suggestions received positive feedback in case of their route planner application. This means that the majority of users do not intend to change travel behavior, but a relatively high effect can be achieved.

It is observed that most users leave feedback on the sustainable transport modes (cycling and public transport), and the number of people who choose car for their urban trips is very low. These results seem to be promising, but there can be a slight bias, as well since regular car drivers, inflexible travelers, or digitally not so advanced users may not even open the application. Thus, it is needed to encourage more drivers and excluded user groups to use the application since the main purpose of using the application is to affect the travel behavior of such users.

The developed web application can effectively support raising awareness campaigns or the elaboration of workplace mobility plans. As an implication of the results, the best transport modes can be suggested, however it has to be validated beyond providing a feedback by the users, whether they would really change their transport mode based on the suggestions of the web application. In order to assess long term travel behavior effects, focus group meetings should explore how individuals react to the direct suggestions of such a tool, and how web applications can support personal goals leading to actual decisions. Thus, considering the practical implications, the web application can be an efficient tool, when developing policies aiming to promote sustainable mode choice. In addition, on the theoretical level, the elaborated utility function and web application provides a good example for the research community, how to suggest the best transport mode considering some relevant parameters. Thus, based on this work more sophisticated results can be produced in the future.

A limitation of the study is the number of feedback messages left by the users in the application. Therefore, it is planned to recruit more people to use the application and encourage them to leave feedback. This can be achieved through the active advertising of the application, awareness campaigns, the implementation of additional persuasive techniques, the introduction of new functions, and the extension of the application in terms of other transport modes.

Another main limitation of the study is that there is no robust evaluation of the impact of the web application related to the foreseen travel behavior change. Due to the limitation of the project scope and budget, further investigation this was not realized. Based on the project goals, the conducted research was not longitudinal, thus the finally selected transport mode was not assessed.

Furthermore, an international comparison might be beneficial, where users with different socio-demographic background, personal preferences, and regular travel behavior might be invited to participate in a global assessment. The application is designed to meet the current standards; thus, it can be applied in any environment. From a technical point of view, the application is capable of expanding its territorial coverage and including other locations as far as map, routing, and timetable information are available.

Some important achievements of the application include the utilization of persuasive strategies and its ability to examine the individual travel preferences for a large number of users. Hence, the application can test the extent to which it might influence travel decisions using soft mobility tools. However, several functionalities are missing from the current application, which may be added in the next phase of the development.

The applied methods in this pilot belong to the soft strategies of changing travel behavior and aim to encourage users to choose sustainable transport modes. However, it is worth pointing out that the persuasive strategies have limitations. In particular, persuasive technologies focus on a specific target behavior and the choices of people instead of offering more collective approaches. This limitation makes "the vision of sustainability" narrow for the reason that social, cultural, and institutional aspects of living are neglected (Dastjerdi et al., 2019).

6. Conclusion

This paper introduces a web-based application which is designed to promote sustainable traveling for daily commuting by using a persuasive tool. An analysis on the intention of travel behavior change in Budapest is performed based on the MoveCit application. The application provides suggestions for the best transport mode choice and asks for feedback from the users.

The main innovation of the developed application is that it is capable to assess the travel preferences of users and thereby help them to choose the most appropriate transport mode (walking, cycling, public transportation, car) considering sustainability. The obtained results give the user a clear picture of the advantages and disadvantages of the various modes of transport in terms of attributes, such as travel time, travel cost, environmental effect, and health effect.

The usability of the web application occurs on multiple levels. On the one hand, based on the feedback of the users, the application is an innovative and well-designed tool for individual travelers to choose the best transport mode for their daily travel routines. On the other hand, from a social point of view, if a sufficiently large number of travelers use the application, the statistical results collected from trip planning can be useful for strategic transport planning and organization processes, such as public transport timetables or car-sharing / car-pooling services.

Highlighting the main results, travelers consider the environmental impact of traveling in an increasing manner during their mode choice decision. In most cases, the application suggests cycling as the best mode choice. This is primarily caused by the fact that users set relatively high weight on travel time, travel cost, and environmental effects, and bike is a very efficient transport mode considering these parameters. In case of registered users, the proportion of providing feedback is much higher than in case of users who do not create a profile. Considering the feedback, almost half of all users agree to choose the best transport mode, which is suggested by the application. The acceptance rate is much higher in case of public transportation and walking. Those users who consider travel time and travel cost as an important influencing factor primarily choose public transportation.

When creating the application, persuasive strategies are applied. Reduction serves to simplify the complex task of mode choice. Attributes which might be set by the users to calculate the best mode choice by the utility function are provided. Tunneling guides the users with a step-by-step approach by providing detailed settings to determine individual travel behavior characteristics and by planning a ranked list of routes for the various transport modes. Suggestion proposes the users the best transport mode based on their personal settings. Personalization offers personalized content to reach better results. Simulation informs the users about the possible consequences of choosing a particular transport mode. Thus, the proposed research provides new insights regarding the application of persuasive technologies to support sustainable transport mode choice. Based on the results, it can be stated that these technologies can be well applied, and users are willing to follow specific suggestions.

Declaration of Competing Interest

None.

Acknowledgement

The paper was prepared within CE25 MOVECIT project, which is supported by Interreg CENTRAL EUROPE Programme funded under the European Regional Development Fund, co-financed by the European Union and the Hungarian State.

The research reported in this paper and carried out at the Budapest University of Technology and Economics has been supported by the National Research Development and Innovation Fund (TKP2020 Institution Excellence Subprogram, Grant No. BME-IE-MISC) based on the charter of bolster issued by the National Research Development and Innovation Office under the auspices of the Ministry for Innovation and Technology.

The linguistic revision of this paper was prepared by Eszter Tóth.

References

Ahmed, S., Adnan, M., Janssens, D., & Wets, G. (2020). A personalized mobility based intervention to promote pro-environmental travel behavior. *Sustainable Cities and Society, 62*, Article 102397. https://doi.org/10.1016/j.scs.2020.102397

Almarsi, E., & Alraee, S. (2013). Factors affecting mode choice of work trips in developing cities—Gaza as a case study. *Journal of Transportation Technologies, 3*, 247–259. https://doi.org/10.4236/jtts.2013.34026

Anagnostopoulou, E., Bothos, E., Magoutas, B., Bradesko, L., Schrammel, J., & Mentzas, G. (2018). Persuasive technologies for sustainable mobility: State of the art and emerging trends. *Sustainability, 10*(7), 2128. https://doi.org/10.3390/su10072128

Anagnostopoulou, E., Urbancic, J., Bothos, E., Magoutas, B., Bradeško, L., & Schrammel, G. (2018). From mobility patterns to behavioural change: Leveraging travel behaviour and personality profiles to nudge for sustainable transportation. *Journal of Intelligent Information Systems, 54*, 157–178. https://doi.org/10.1007/s10844-018-0528-1

Andersson, A., Hiselius, L. W., & Adell, E. (2018). Promoting sustainable travel behaviour through the use of smartphone applications: A review and development of a conceptual model. *Travel Behaviour and Society, 11*, 52–61. https://doi.org/10.1016/j.tbs.2017.12.008

Bamberg, S., Fujii, S., Friman, M., & Gärling, T. (2011). Behaviour theory and soft transport policy measures. *Transport Policy, 18*(1), 228–235. https://doi.org/10.1016/j.tranpol.2010.08.006

Bamberg, S. (2013). Applying the stage model of self-regulated behavioral change in a car use reduction intervention. *Journal of Environmental Psychology, 33*, 68–75. https://doi.org/10.1016/j.jenvp.2012.10.001

Ben-Akiva, M., & Bierlaire, M. (1999). Discrete choice methods and their applications to short term travel decisions. In *Handbook of transportation science, international series in operations research & management science, 23* pp. 5–33). Boston, MA: Springer. https://doi.org/10.1007/978-1-4615-5203-1_2

Bhatt, K., Higgins, T., & Berg, J. T. (2008). *Lessons learned from international experience in congestion pricing (No. FHWA-HOP-08-047)*. K.T. Analytics Inc.. Final Report.

Bothos, E., Prost, S., Schrammel, J., Röderer, K., & Mentzas, G. (2014). Watch your emissions: Persuasive strategies and choice architecture for sustainable decisions in urban mobility. *PsychNology Journal, 12*(3), 107–126.

Cascetta, E. (2009). Random utility theory. In E. Cascetta (Ed.), *Transportation systems analysis* (pp. 89–167). Boston: Springer. https://doi.org/10.1007/978-0-387-75857-2_3.

Dastjerdi, A. M., Kaplan, S., Silva, J. A., Nielsen, O. A., & Pereira, F. C. (2019). Use intention of mobility-management travel apps: The role of users' goals, technophile attitude and community trust. *Transportation Research Part A, 126*, 114–135. https://doi.org/10.1016/j.tra.2019.06.001

De Vos, J., Mokhtarian, P. L., Schwanen, T., Van Acker, V., & Witlox, F. (2016). Travel mode choice and travel satisfaction: Bridging the gap between decision utility and experienced utility. *Transportation, 43*, 771–796. https://doi.org/10.1007/s11116-015-9619-9

Di Dio, S., Gennusa, M. L., Peri, G., Rizzo, G., & Vinci, I. (2018). Involving people in the building up of smart and sustainable cities: How to influence commuters' behaviors through a mobile app game. *Sustainable Cities and Society, 42*, 325–336. https://doi.org/10.1016/j.scs.2018.07.021

Eboli, L., & Mazzulla, G. (2010). How to capture the passengers' point of view on a transit service through rating and choice options. *Transport Reviews, 30*(4), 435–450. https://doi.org/10.1080/01441640903068441

Ferguson, C. (2016). Managing and motivating sustainable travel behaviour change. In S. Biermann, D. Olaru, & V. Paul (Eds.), *Planning boomtown and beyond* (pp. 592–615). UWA Publishing.

Giuliano, G., & Hanson, S. (2017). *The geography of urban transportation* (4th edition). New York: The Guilford Press. ISBN 9781462529650.

Gössling, S. (2017). ICT and transport behaviour: A conceptual review. *International Journal of Sustainable Transportation, 12*(3), 153–164. https://doi.org/10.1080/15568318.2017.1338318

Gudmundsson, H., Hall, R. P., Marsden, G., & Zietsman, J. (2016). Transportation and sustainability, sustainable transportation. *Springer texts in business and economics*. Berlin, Heidelberg: Springer. https://doi.org/10.1007/978-3-662-46924-8_4

Günther, M., Kacperski, C., & Krems, J. F. (2020). Can electric vehicle drivers be persuaded to eco-drive? A field study of feedback, gamification and financial rewards in Germany. *Energy Research & Social Science, 63*, Article 101407. https://doi.org/10.1016/j.erss.2019.101407

Hasnine, M. D., Lin, T., Weiss, A., & Habib, K. N. (2018). Determinants of travel mode choices of post-secondary students in a large metropolitan area: The case of the city of Toronto. *V Journal of Transport Geography, 70*, 161–171. https://doi.org/10.1016/j.jtrangeo.2018.06.003

Hilgert, T., Weiss, C., Kagerbauer, M., Chlond, B., & Vortisch, P. (2016). Stability and flexibility in commuting behavior: Analyses of mode choice patterns in Germany [Paper Numbers: 16-2637]. In *Transportation research board 95th annual meeting*.

INTERREG Central Europe (2019). MoveCit project, Retrieved April 30, 2020. URL: https://www.interreg-central.eu/Content.Node/MOVECIT.html.

Iordanopoulos, P., Mitsakis, E., & Chalkiadakis, C. (2018). Prerequisites for further deploying ITS systems: The case of Greece. *Periodica Polytechnica Transportation Engineering, 46*(2), 108–115. https://doi.org/10.3311/PPtr.11174

Klöckner, C. A., & Blöbaum, A. (2010). A comprehensive action determination model: Toward a broader understanding of ecological behaviour using the example of travel mode choice. *Journal of Environmental Psychology, 30*(4), 574–586. https://doi.org/10.1016/j.jenvp.2010.03.001

Koppelman, F. S. (1981). Non-linear utility functions in models of travel choice behavior. *Transportation, 10*, 127–146. https://doi.org/10.1007/BF00165262

Kwan, S. C., Sutan, R., & Hashim, J. H. (2018). Trip characteristics as the determinants of intention to shift to rail transport among private motor vehicle users in Kuala Lumpur, Malaysia. *Sustainable Cities and Society, 36*, 319–326. https://doi.org/10.1016/j.scs.2017.10.030

Li, S., & Zhao, P. (2015). The determinants of commuting mode choice among school children in Beijing. *Journal of Transport Geography, 46*, 112–121. https://doi.org/10.1016/j.jtrangeo.2015.06.010

Lind, H. B., Nordfjærn, T., Jørgensen, S. H., & Rundmo, T. (2015). The value-belief-norm theory, personal norms and sustainable travel mode choice in urban areas. *Journal of Environmental Psychology, 44*, 119–125. https://doi.org/10.1016/j.jenvp.2015.06.001

Long, J. S. (1997). *Regression models for categorical and limited dependent variables*. Thousand Oaks, United States: SAGE Publications. ISBN: 9780803973749.

Martin, A., Suhrcke, M., & Ogilvie, D. (2012). Financial incentives to promote active travel: An evidence review and economic framework. *American Journal of Preventive Medicine, 43*(6), 45–57. https://doi.org/10.1016/j.amepre.2012.09.001

Minal, S., & Ravi Sekhar, C. (2014). Mode choice analysis: The data, the models and future ahead. *International Journal for Traffic and Transport Engineering, 4*(3), 269–285. https://doi.org/10.7708/ijtte.2014.4(3).03

Morris, E. A., & Guerra, E. (2015). Mood and mode: Does how we travel affect how we feel? *Transportation, 42*(1), 25–43. https://doi.org/10.1007/s11116-014-9521-x

Muro-Rodríguez, A. I., Perez-Jiménez, I. R., & Gutiérrez-Broncano, S. (2017). Consumer behavior in the choice of mode of transport: A case study in the Toledo-Madrid Corridor. *Frontiers in Psychology, 8*(1011). https://doi.org/10.3389/fpsyg.2017.01011

Myrovali, G., Morfoulaki, M., Vassilantonakis, B.-M., Mpoutovinas, A., & Kotoula, K. M. (2020). Travelers-led innovation in sustainable urban mobility plans. *Periodica Polytechnica: Transportation Engineering, 48*(2), 126–132. https://doi.org/10.3311/PPtr.11909

Nasrudin, N., Ayu Abdullah, Y., & Ling Hoon Leh, O. (2017). Promoting sustainable travel behavior through transport policy measures. *Journal of the Malaysian Institute of Planners, 15*(2), 85–96. https://doi.org/10.21837/pmjournal.v15.i2.270

Ng, W.-S. (2018). Urban transport mode choice and carbon emissions in Southeast Asia. *Transportation Research Record: Journal of the Transportation Research Board, 2672*(2), 54–67. https://doi.org/10.1177/0361198118797213

Olsson, L. E., Huck, J., & Friman, M. (2018). Intention for car use reduction: Applying a stage-based model. *International Journal of Environmental Research and Public Health, 15*(2), 216. https://doi.org/10.3390/ijerph15020216

Ortuzar, J. D., & Willumsen, L. G. (2011). *Modelling transport* (4th edition). Oxford, United Kingdom: Wiley. ISBN 9781119993315.

Sun, R., Li, M., & Wu, Q. (2018). Research on commuting travel mode choice of car owners considering return trip containing activities. *Sustainability, 10*(10), paper 3494. https://doi.org/10.3390/su10103494

Sunio, V., & Schmöcker, J.-D. (2017). Can we promote sustainable travel behavior through mobile apps? Evaluation and review of evidence. *International Journal of Sustainable Transportation, 11*(8), 553–566. https://doi.org/10.1080/15568318.2017.1300716

Sunio, V., Schmöcker, J. D., & Kim, J. (2018). Understanding the stages and pathways of travel behavior change induced by technology-based intervention among university students. *Transportation research part F: Traffic psychology and behaviour, 59*, 98–114. https://doi.org/10.1016/j.trf.2018.08.017

Tajalli, M., & Hajbalaie, A. (2017). On the relationships between commuting mode choice and public health. *Journal of Transport & Health, 4*, 267–277. https://doi.org/10.1016/j.jth.2016.12.007

Yang, Y., Wang, C., Liu, W., & Zhou, P. (2018). Understanding the determinants of travel mode choice of residents and its carbon mitigating potential. *Energy Policy, 115*, 486–493. https://doi.org/10.1016/j.enpol.2018.01.033

Zong, W., & Zhang, J. (2019). Use of smartphone applications and its impacts on urban life: A survey and random forest analysis in Japan. *Sustainable Cities and Society, 49*, Article 101589. https://doi.org/10.1016/j.scs.2019.101589