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Mohsen MAKAREMI-SHARIFI[1], Amir Abbas RASSAFI[2]

THE PREFERENCES OF CHOOSING TAXI-HAILING MODE ATTRIBUTES THROUGH THE BWS-CASE 1

Summary. With the widespread use of the Internet in everyday life, new businesses have emerged, causing significant changes in the market, while some traditional businesses were marginalized. One of the emerging businesses is taxi-hailing, which has gained popularity among the public. This study examines ten attributes of taxi-hailing and asks individuals about their preferences for these attributes through a questionnaire. Unlike the traditional approach of dealing with discrete choice models, which focuses on choosing the best (most important) alternative only, the role of the worst (least important) alternative is also considered in this type of modelling. The present study utilizes case 1 (out of the three available cases) of this scaling method, called “best-worst”, which focuses on attributes. Each questionnaire includes 12 questions about taxi-hailing attributes, where respondents have to state their preference in selecting the best and the worst ones. The results indicate that security and reassurance are the most crucial attributes when deciding this transportation mode, followed by accessibility. Compliance with health issues and social distancing ranked as the least significant attribute.

Keywords: taxi-hailing attributes, best worst scaling, discrete choice model, stated preference

[1] Faculty of Engineering, Imam Khomeini International University, Qazvin, Iran.
Email: m.makaremi.sh@gmail.com. ORCID: https://orcid.org/0009-0002-3545-2069
[2] Faculty of Engineering, Imam Khomeini International University, Qazvin, Iran. Email: rasafi@eng.ikiu.ac.ir.
ORCID: https://orcid.org/0000-0002-3419-0194

1. INTRODUCTION

The impact of the Internet on people's lives has been immense, and one of the significant changes it has brought about is the emergence of new businesses, including taxi-hailing services. Uber, a US-based transportation company, has been highly successful in this field and has inspired similar companies in other countries. In Iran, for the first time in mid-2014, people were able to use their smartphones to book rides, from a company called “Snapp”, and avoid the hassle of either calling taxi companies, or finding taxis in the streets. The popularity of this new transportation mode led to the emergence of other taxi companies in the country.

This study aims to determine what aspects of taxi-hailing, from the users' standpoint, are more crucial and contribute to its growth and significance. Consequently, the primary focus of this study is to uncover answers to the following questions:

1. What are the effective attributes in choosing a taxi-hailing?
2. What will the effect of different attributes be in selecting a taxi-hailing?

Discrete choice models are highly beneficial in studying, simulating, and rationalizing passengers' preferences. They can estimate the likelihood of decision-makers selecting from various alternatives and their decision-making behavior. These models adopt a probabilistic structure to mathematically model the decision-makers’ behavior and their attempts to maximize the utility resulting from their choice. The probability model arises from the presence of an unknown or error term in the analyst's understanding. Depending on the distribution assumption made for this error, different models can be employed, among which, the logit model is the most commonly used.

The Best-Worst Scaling (BWS) Case 1 method has been utilized as a ground-breaking approach to studying discrete choice. This technique places emphasis on both the best and worst alternatives, thereby underscoring the importance of attributes in the selection process like never before.

The rest of this paper is organized as follows: Section 2 provides a concise overview of the research background, while section 3 discusses the methodology employed in this study. Then, the research findings and Conclusions are described in Section 4. and Section 5, respectively. References are given in section 6.

2. LITERATURE REVIEW

This following review covers several studies focused on various aspects of the taxi-hailing. These studies explore topics such as the impact of technology on the industry, the design of a more efficient taxi management system, the influence of social media on travel behavior, and the factors that affect the adoption of on-demand ride-hailing services.

The taxi industry is being reformed due to advancements in network technology and operational thinking brought on by the new era of the Internet. The introduction of special cars has had an unprecedented impact on the industry. Li examined the market positioning and operation mode differences between taxis and special cars by analyzing their positioning in domestic and foreign cities, as well as industrial development mode experience. He explored the possibility of their harmonious development and suggested specific proposals for the development and management of the taxi industry. He believes that service quality should always be considered the most important evaluation criterion [1].

Taxis are a convenient mode of transportation for many people. However, the common ways of finding passengers, either by driving around or staying at designated spots, are inefficient and wasteful. They lead to low occupancy rates and various issues such as traffic congestion and environmental damage. Dow *et al.* proposed a taxi management system using Location-Based Services and regional queuing techniques on the Internet. In this proposed system, the service areas are defined based on the geogrid and enable drivers to hunt both in the streets and wait in a station. They conducted field research on actual taxi operations and used PRISM to simulate and compare their model with the waiting model. The results indicated that their model is more efficient than the waiting model. In the field research, they designed a questionnaire for taxi drivers and examined a taxi station in Taiwan to obtain logical, empirical data. Although the modelling results show the superiority of the proposed model over the traditional models, this modelling was only based on approximately 30 effective questionnaires [2].

The study of how travelers decide to move around has always been important in transportation research. With the increasing availability of ICT in everyday life, the context in which people make travel decisions has changed. Regardless of whether travelers are intentionally searching for information before their trip or casually browsing the internet, they can find user-created content on social media that could potentially influence the decisions they make about how to move around. Bou Mjahed *et al.* examined trip behavior in a highly connected environment and attempted to design tools based on ICT to influence behaviors. They studied how a platform called Yelp.com (a multinational company in the US that helps people find local businesses) can provide information for activities and trip planning in the pre-trip process. The work presented in this study could be valuable as a starting point for more profound research on social media platforms and their role in trip planning and trip behavior [3].

The study by Chen *et al.* used online Location-Based Services network data from Brighticket to examine the effect of social networks on passengers' destination choices in the Chicago metropolitan area1. The study found that social connections have a significant impact on travelers' destination selection1. The formation of destination choice sets is influenced not only by external factors but also by personal perceptions, attitudes, and acceptance. Consequently, for an accurate understanding and prediction of daily trip demand, it is important to consider this process dynamically. The study found that social connections have a significant impact on travelers' destination selection, and that the quantity of virtual friends has a substantial impact on actual physical travel behavior. However, the dataset used in this study has some constraints such as no data available on socio-demographic characteristics like age, ethnicity, etc., not all entries are logged and home and work locations are not differentiated [4].

Alemi *et al.* investigated the factors that influence the adoption of on-demand ride-hailing services such as Uber and Lyft among Millennials (i.e., individuals born between 1981 and 1997) and Generation X (i.e., middle-aged adults between 1965 and 1980) in California. They found that educated and older millennials are more likely to use on-demand ride-hailing services than other groups. Additionally, mixed land use and regional access by car are linked to a higher probability of accepting on-demand ride-hailing services. Participants who reported a higher frequency of long-distance trips and a higher proportion of long-distance trips by plane, as well as regular users of transportation-related smartphone apps and those who had previously used taxi and car-sharing services, were more likely to use these services. These findings can serve as a foundation for predicting the adoption of on-demand services and their impact on general behavioral patterns across different regions and social and demographic variables [5].

Song studied the impact of the emergence of new modes of transportation in changing mode choice behavior. Considering that a new mode is usually associated with some new attributes that people may be less familiar with, she tried to investigate the mode choice behavior by collecting data through stated preference and discrete choice modelling at the individual level and uncovering travel demand through empirical analysis. Using best-worst scaling, she investigated people's behavior in choosing two new modes of HSR (high-speed rail)-air and air taxi service [6].

The level of security has a significant impact on people's mobility. Jing *et al.* discussed the challenges faced by service providers in ensuring security during taxi-hailing trips, particularly following incidents of sexual assault and homicide. Didi Taxi-hailing Company has implemented additional measures to enhance passenger security, but there are few scientific findings on the effect of these measures on personal perception of security. They identified the key underlying factors that impact individuals' willingness to use or reuse taxi-hailing services following modifications to their security measures by expanding and merging the Technology Acceptance Model (TAM) and the Theory of Planned Behavior. Notably, the level of security risks and perceived security have a significant impact on their behavioral intentions. On the contrary, the impact of government credit is not immediate. The trust levels can be affected by government credit, which in turn indirectly impacts the intention to use. Ultimately, this research affirms that investigating the impact of latent factors on the utilization or reutilization of taxi-hailing services can enhance the evaluation and improvement of security measures [7].

In Iran, Akbari *et al.* built a model combining the TAM with the information and trust system success model to determine the factors impacting the level of acceptance of users of taxi-hailing services. This study involved approximately 500 individuals from Tehran, from which 466 acceptable answers were obtained. The data was analyzed using a mediating analysis in a structural equation model. The study revealed that the perceived ease of use and perceived usefulness are significantly influenced by the quality of information and services. As anticipated, trust was positively associated with both perceived usefulness and perceived ease of use, while behavioral intention was positively linked to perceived usefulness. However, the predicted positive relationship between perceived ease of use and the behavioral intention was rejected. In addition, the outcomes of this investigation demonstrate that trust plays a crucial part as a mediator in the model. By exploring the mediating function of trust, an area that has not been previously investigated, this study broadens the technology adoption literature. The research focused on how trust primarily enhances the inclination to utilize a taxi-hailing service, ultimately influencing the likelihood of selecting this mode[8].

Louviere and Woodworth were the first to propose a discrete choice framework in which, in addition to the traditional determination of the best alternative in a set of choices, a person is asked to indicate the least important alternative in that set. This data collection method is called BWS and is used in many fields [9].

Louviere and Flynn wrote a book for researchers and practitioners who have some background and basic knowledge of BWS. They showed that BWS is accessible to a practitioner with moderate application skills and, often, can be successfully implemented using spreadsheet software rather than statistical programs. In this book, they brought together theories and methods and demonstrated their application in various case studies in a useful reference guide [10].

Lancsar *et al.* revealed that the primary objective of Discrete Choice Experiments (DCEs) is to gather high-quality choice data for estimating choice models, which can be utilized to investigate health-related experiments. The study introduced a novel type of choice experiment called Best Worst Discrete Choice Experiments. The authors explained what the approach is, how and when to use it, and provided some analytical methods for modelling the available data. In an experimental program, the approach for preference extraction was tested by investigating the preferences of 898 individuals in Edmonton and Calgary, Canada, whose topic was the treatment of cardiac arrest that occurred in a public place, and showed that better results are obtained compared to traditional analysis [11].

He and Shen proposed a spatial equilibrium model that not only balances the supply and demand of taxi services but also captures both the taxi drivers' and passengers' possible adoption of the newly emerging e-hailing applications in a well-regulated taxi market. They then proved the existence of the proposed equilibrium, and further provided an algorithm to solve it. They also suggested an extensive equilibrium model with elastic taxi-passenger demands. Lastly, they presented a numerical example to compare the taxi services with and without the e-hailing application and evaluated two types of e-hailing applications [12].

Lancsar *et al.* have also offered instructions for users on how to interpret data obtained from DCEs using the best-worst and best-best data approaches. This guide contains a theoretical overview of the major choice models, as well as practical tips on interpreting and using the results of the analysis. They also provide descriptions of standard software that can be used in these methods. In this guide, in addition to providing descriptions of choice modelling, they attempt to do so in a way that allows researchers to analyze the data. They argued that the choice of modelling method depends on the research questions, study design, and limitations in terms of data quality/quantity and that decisions made regarding the choice of data analysis are often mutually dependent instead of being sequential. Additionally, they hold the belief that the knowledge and application presented in this research can be advantageous for scholars not only in the field of health economics but also in other areas [13].

Echaniz *et al.* also showed that overall customer satisfaction with the public transportation system mainly depends on two factors: The degree of contentment a customer feels regarding various elements of the service, as well as the significance that each of those elements holds for the customer. Typically, researchers utilize revealed preference surveys along with logit/probit models to gauge the proportion of satisfaction associated with each service characteristic in the conventional approach. The study's objective was to explore the feasibility of replacing the conventional technique with BWS-case 1. Through a customer survey conducted in Santander, Spain, they demonstrated that the satisfaction level obtained from both methods is quite comparable. However, due to the distinct relative significance of each attribute obtained from these two approaches, they inferred that the best-worst method offers more insightful and reliable findings that align with the existing literature on public transportation customer satisfaction [14].

A common goal in psychological research is to measure subjective perceptions, such as the first perception of a face. These perceptions are usually measured using a Likert scale. Although these ratings are simple to implement, they come with responses that can limit validity. Burton *et al.* studied BWS as an alternative to the Likert scale to measure participants' first facial perceptions. They found that BWS scores were almost perfectly correlated with Likert scores at the group level, suggesting that the two methods have the same perceptions. However, at the level of individual participants, it outperforms Likert scale both in terms of its ability to predict preferences and in terms of validity test. These advantages make the power of BWS exceptional, especially for use in individual differences research [15].

Aizaki *et al.* have published several works about the application of BWS in the field of agriculture, instructions on how to perform different cases of BWS and how to use relevant packages in R software by mentioning illustrative examples. They have presented the latest version of a package called support.BWS that can be utilized for such studies and explained its functions [16-18].

In conclusion, by incorporating ICT, we can gather more accurate data and develop more effective transportation policies. As technology continues to evolve, it presents exciting opportunities for improving our transportation systems and enhancing the quality of life for individuals and communities. With the emergence of taxi-hailing platforms, such as Uber and Lyft, commuters have access to an affordable, convenient, and reliable mode of transportation. By integrating technology like ICT into daily travel, the benefits of the BWS method can be further amplified, resulting in more efficient and sustainable travel experiences for everyone. Tab. 1 has summarized the reviewed literature.

Tab. 1

Summary of the literature review

Researchers	**year**	**Dealing with the subject**					
		Transition in traditional taxis	**Internet, application**	**Taxi - hailing**	**Best-worst scaling**	**Stated preference**	**Revealed preference**
Louviere and Woodworth	1990				✓	✓	
Lancsar *et al.*	2013				✓	✓	
Aizaki *et al.*	2014				✓	✓	
He and Shen	2015	✓	✓	✓			✓
Lancsar *et al.*	2017				✓	✓	
Li	2016	✓	✓				
Dow *et al.*	2016	✓	✓				✓
Bou Mjahed *et al.*	2017		✓				✓
Chen *et al.*	2018		✓				✓
Alemi *et al.*	2018		✓	✓			✓
Echaniz *et al.*	2019				✓	✓	
Burton *et al.*	2019				✓	✓	
Aizaki and Fogarty	2019				✓	✓	
Song	2019	✓			✓	✓	
Akbari *et al.*	2020			✓		✓	
Jing *et al.*	2021			✓		✓	
Aizaki and Fogarty	2023				✓	✓	

3. METHODOLOGY

The proposed methodology involves the following steps. Firstly, the variables representing taxi-hailing attributes are determined, encompassing factors such as time and cost. Secondly, the study area is identified. Then, sample size is determined, considering a random sampling of individuals with taxi-hailing experience in the chosen area. To ensure efficient data collection and analysis, an experimental design of Orthogonal Main Effects Design is employed. This design systematically varied attribute levels across choice tasks. The questionnaire is then designed, incorporating choice tasks that presented different attribute combinations. After analyzing the collected data, the collected data underwent preparation for modelling, including cleaning, coding, and formatting. Modelling techniques, i.e., logit models and counting approach are applied to estimate preference weights and identify significant factors. The research results are derived from the analysis, including estimated preference weights and their significance. Finally, the methodology is concluded. These steps are briefly shown in the flowchart of Fig. 1. and further explained in the subsections.

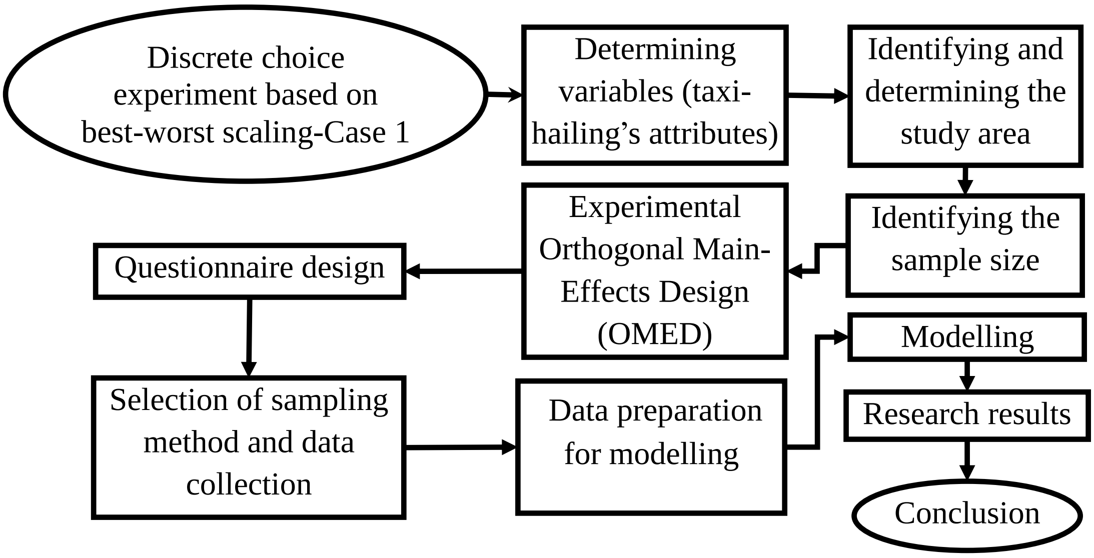

Fig. 1. The flowchart of the research methodology

3.1. DCEs

DCEs method is a preferred approach that involves generating and analyzing choice data. They are usually conducted in surveys. This survey presents the participants with multiple sets of choices, each comprising various questions, and the participants are required to select one alternative from each set.

3.2. Discrete choice model

Discrete choice modelling is one of the important components of DCE that researchers face when analyzing DCE data in a situation where the study level is disaggregated. Certain decisions should be made regarding the model structure (binary vs. multiple choices; linear, quadratic, logarithmic, etc.; …) based on the nature of the problem at hand. Hence, it is not possible to suggest a single model that is suitable for all situations. Each model has its strengths and weaknesses depending on the particular research problem. It is crucial to bear in mind that the selection of a model is influenced by factors such as study goals, research questions study design, and data availability.

Multinomial Logit (MNL) and its associated theory (i.e., random utility developed by [19]) are typically a starting point for the discrete choice models. The utility shown in Equation (1) is received for respondent i who chooses alternative j in choice scenario s:

$$U_{isj} = V_{isj} + \varepsilon_{isj},\ i = 1, \dots, N;\ \ s = 1, \dots, S;\ \ j = 1, \dots, J \tag{1}$$

Where *N* decision makers choose *J* alternatives among *S* scenarios. V_{isj} and ε_{isj} represent the systematic or predictable component of the overall utility of choosing alternative *j* in scenario *s* by decision maker *i*, and the potential disturbance (error) term represents attributes that are unobservable by the analyst, respectively. It is assumed that decision maker *i* chooses alternative *j* if it provides the highest utility compared to the utility associated with the other alternatives in the choice set. Therefore:

$$P_{isj} = Prob(U_{isj} - U_{isl} > 0),\ \forall l \neq j \tag{2}$$

Where P_{isj} is the probability of choosing alternative *j* in scenario s by individual *i*. In the well-known MNL format, the likelihood of selecting j can be expressed in the following:

$$P_{isj} = \frac{\exp(\lambda\, \mathrm{V_{isj}})}{\sum_{\mathrm{l=1}}^{\mathrm{J}} \exp(\lambda\, \mathrm{V_{isl}})} \tag{3}$$

Where λ represents the scale parameter, which is the inverse of the disturbance's standard deviation. However, in the standard MNL model, λ cannot be determined and is typically set to one. In the Conditional Logit (CL) model, the independent variables change based on the attributes of different alternatives. In this method, the analysis is done on a set of different alternatives for each person. At the same time, in the MNL model, the independent variables are the attributes of each person. In other words, to distinguish between conditional logit and MNL models, the question can be raised whether the independent variables change with choices. If the answer is negative, the multinomial logit model should be used, and if the answer is positive, the conditional logit model should be used.

One of the important requirements in using the conditional logit and multinomial logit models is that the choice of alternatives from a choice set should follow the attribute of independence from irrelevant alternatives. This implies that the likelihood ratio linked to the other alternatives remains unaffected by the existence or non-existence of an alternative.

3.3. Scaling of the BWS-Case 1

In examining the structure of this model, an attempt is made to improve the stated preference results by using techniques, among which is the BWS, which is based on the idea that a person, among a set of alternatives, identifies the best and worst alternatives of the set. BWS consists of three cases, which differ only in the complexity of the cases or alternatives considered. In Case 1 (object case), the respondents evaluate the list of attributes and then subsets of those attributes are presented to them as a choice set. They are asked to select the most and the least important cases from each subset. This process is repeated until all subsets have been evaluated. In Case 2 (profile case), different combinations of profile levels are created and respondents are asked to select the best and worst levels for each profile. Case 3 (multiprofile case) involves respondents selecting the best and worst profiles from a choice set of three or more profiles.

3.4. Determining the variables (Taxi-hailing attributes)

In the first step an attempt was made to determine the significant attributes in choosing taxi-hailing with the benefit of scientific studies. After a careful review, ten distinct attributes were identified in this category. These attributes include:

1. Cost

2. Convenience
3. Safety against risks
4. Security and confidence
5. Honoring the customer
6. Compliance with health cares and social distancing
7. Being fast
8. Accessibility
9. Flexibility (in terms of time and choice of intermediary destination, etc.)
10. Dependence on technology (cell phone and Internet)

3.5. Identification and determination of the study area

The study area is Qazvin city, the provincial capital of Qazvin province. Qazvin province, with an area equivalent to 15623 km^2 in the central area of Iran, is placed between 48° 44' to 50° 51' longitude and 35° 24' to 36° 36' latitude (See Fig. 2.). Qazvin province is bordered by Guilan and Mazandaran provinces from the north, Hamadan and Zanjan provinces from the west, Markazi province from the south, and Alborz province from the east. This province is made up of 20 cities in the form of 5 counties and the National Statistics Centre of Iran has announced the population of Qazvin province as 1326400 people and the population of Qazvin County as 621800 people by the end of 2021.

Fig. 2. Map of Qazvin province

3.6. Sample size

Since best-worst scaling introduces a different choice task with distinct outcomes compared to conventional DCEs, the sample sizes necessary for estimating disaggregated utilities remain uncertain. Nevertheless, according to Flynn *et al.*, if the focus lies on comparing the proportions of respondents selecting different attribute levels, it is possible to estimate the required sample sizes using equations for confidence intervals. In these cases, factors such as the number of times the best-worst pairs are chosen are used [20]. Although there are no specific methods for determining sample size for B-W scaling, according to Louviere *et al.*, sample size determination techniques used for multinomial proportions data can be applied [21, 22].

Thompson established sample size requirements for multinomial proportions data, with deriving a formula that determines the necessary sample size based on the acceptable level of error and desired level of confidence for obtaining population proportions. He devised a method for determining the necessary sample size for multinomial proportions data. Similar to the binomial case, the sample size is dependent on the acceptable error level (α) and the desired confidence level (d) of the actual population proportions. Thompson found that the number of multinomial categories (j or alternatives) does not affect the required sample size. He created a table to aid in determining the appropriate sample size based on the desired values of α and d. As an illustration, Thompson gave the example of a biologist who wants to estimate the proportion of fish in each age class in a population. To achieve a probability of 0.95 that all estimates are within 0.05 of the population proportion, a sample size of 510 would suffice [22].

If the BWS considerations are not taken into account, it is proposed that 384 observations are needed using Cochran's formula [23]. This estimation is based on the latest population and housing census in 2016, which reported the population of Qazvin city to be approximately 600,000 people. In this study, 100 questionnaires were collected, in which 12 different scenarios were asked in each questionnaire, and a total of 1200 observations were obtained. Therefore, with this number of observations, the assurance of the required sample size was provided [22].

3.7. Orthogonal Main Effects Design (OMED)

A well-planned experimental design results in the most accurate estimations. The arrangement of variables that have a significant impact on the analysis is determined by the analyst, highlighting the crucial role of analysts in designing the experiment. For example, if there is an effect between attributes identified.

In this study, the OMED design was used. Since even a few number of factors and a few levels per factor lead to an unmanageable number of potential profiles, a representative subset, known as an orthogonal array, must be generated. Orthogonal design provides the possibility to examine the main and interaction effects by performing the least number of experiments. In an OMED, the levels of each factor are chosen so that they are orthogonal to each other. This means that the effect of each factor can be estimated independently of the other factors. Furthermore, each row corresponds to a question and each column corresponds to an item. Each element in the matrix is assigned one of two distinct numbers. One value represents the item being “absent” from the corresponding column, while the other value represents the item being “present.” This allows researchers to decide which items are assigned to each question [16]. To prepare the questionnaire based on this design, the desired experiment was designed by utilizing the oa.design function from the R software's DoE.base package.

3.8. Questionnaire design

Using the OMED design, a set of choices was made to ask the respondents; in each question, a set of several attributes was presented and simultaneously exposed to the choice of the most important and the least important alternative to pick. In this test design, each respondent was asked 12 questions, and in each question, the attributes were appeared according to Fig. 3.

3.9. Selection of sampling method and Data collection

In order to collect the required information, questionnaires were designed and prepared electronically, and its hyperlink was distributed in social networks whose members were from different age ranges. The questionnaire included questions about individual attributes (age, gender, education, job, etc.) and questions to discover the best-worst priorities among the alternatives and attributes.

After designing the questionnaire questions, the survey form was created as an online form, and its hyperlink was provided to 100 respondents. The reasons for choosing this number were discussed in section 3.6. After completing the survey, the response data was converted, which consists of the respondents' choices as the best and worst alternatives from each choice set, into data that can be used for modelling in R software. Tab. 2 displays a dataset whose first column includes the variable ID, the unique identification number of the participant. The following columns show pairs of response variables, where each pair indicates the participant's choice of the best and worst attributes for each question.

```
Q1
 Best Items                 Worst
 [ ]  Convenience           [ ]
 [ ]  Honoring the customer [ ]
 [ ]  To be fast            [ ]
 [ ]  accessibility         [ ]
 [ ]  flexibility           [ ]

Q2
 Best Items                     Worst
 [ ]  cost                      [ ]
 [ ]  Safety against risks      [ ]
 [ ]  Security and confidence   [ ]
 [ ]  Honoring the customer     [ ]
 [ ]  flexibility               [ ]

Q3
 Best Items                      Worst
 [ ]  Convenience                [ ]
 [ ]  Security and confidence    [ ]
 [ ]  Honoring the customer      [ ]
 [ ]  health care                [ ]
 [ ]  Dependence on technology   [ ]

Q4
 Best Items                     Worst
 [ ]  cost                      [ ]
 [ ]  Security and confidence   [ ]
 [ ]  health care               [ ]
 [ ]  To be fast                [ ]
 [ ]  accessibility             [ ]

Q5
 Best Items                      Worst
 [ ]  cost                       [ ]
 [ ]  Convenience                [ ]
 [ ]  Safety against risks       [ ]
 [ ]  To be fast                 [ ]
 [ ]  Dependence on technology   [ ]

Q6
 Best Items                      Worst
 [ ]  Security and confidence    [ ]
 [ ]  To be fast                 [ ]
 [ ]  flexibility                [ ]
 [ ]  Dependence on technology   [ ]

Q7
 Best Items                      Worst
 [ ]  cost                       [ ]
 [ ]  Convenience                [ ]
 [ ]  Safety against risks       [ ]
 [ ]  Security and confidence    [ ]
 [ ]  Honoring the customer      [ ]
 [ ]  health care                [ ]
 [ ]  To be fast                 [ ]
 [ ]  accessibility              [ ]
 [ ]  flexibility                [ ]
 [ ]  Dependence on technology   [ ]

Q8
 Best Items        Worst
 [ ]  cost         [ ]
 [ ]  Convenience  [ ]
 [ ]  health care  [ ]
 [ ]  flexibility  [ ]

Q9
 Best Items                   Worst
 [ ]  Safety against risks    [ ]
 [ ]  Honoring the customer   [ ]
 [ ]  health care             [ ]
 [ ]  To be fast              [ ]

Q10
 Best Items                      Worst
 [ ]  Safety against risks       [ ]
 [ ]  health care                [ ]
 [ ]  accessibility              [ ]
 [ ]  flexibility                [ ]
 [ ]  Dependence on technology   [ ]

Q11
 Best Items                     Worst
 [ ]  Convenience               [ ]
 [ ]  Safety against risks      [ ]
 [ ]  Security and confidence   [ ]
 [ ]  accessibility             [ ]

Q12
 Best Items                      Worst
 [ ]  cost                       [ ]
 [ ]  Honoring the customer      [ ]
 [ ]  accessibility              [ ]
 [ ]  Dependence on technology   [ ]
```

Fig. 3. Questionnaire design using OMED

3.10. Data preparation for modelling

The data is prepared for modelling according to Tab. 3. For example, in question 1 of the respondent 1, five attributes (ITEMs 2, 5, 7, 8, and 9) are available for selection. Therefore, there are a total of 20 best-worst combinations for this query. This respondent chose ITEM8 as the best, and ITEM9 as the worst attribute. In each row of this table each attribute takes the value of 1 if it is chosen as the best, value of -1 if it is chosen as the worst, and 0 otherwise.

Tab. 2

Data entry for the attributes chosen in each question by the respondents

	ID	B 1	W 1	B 2	W 2	B 3	W 3	B 4	W 4	B 5	W 5	B 6	W 6	B 7	W 7	B 8	W 8	B 9	W 9	B 10	W 10	B 11	W 11	B 12	W 12
1	1	4	5	1	3	5	2	5	2	5	3	4	1	8	4	2	4	4	1	5	1	4	3	4	1
2	2	4	3	5	1	4	1	5	1	5	1	3	2	9	1	3	1	3	4	4	1	4	1	3	1
3	3	3	4	3	1	1	5	4	1	4	1	2	4	4	1	4	1	4	1	3	1	3	2	3	1
4	4	4	2	1	4	2	3	2	4	3	4	3	4	4	10	1	4	1	4	3	5	3	4	1	2
5	5	4	5	1	5	5	4	5	3	1	3	2	3	1	6	1	3	4	3	3	2	4	2	1	2
6	6	2	4	1	5	2	5	4	5	3	4	3	2	1	2	1	4	1	4	1	4	2	4	1	4
7	7	1	5	1	5	1	5	1	4	1	5	1	4	1	10	1	4	4	3	3	4	1	4	1	4
8	8	4	5	1	5	1	3	1	3	1	5	1	4	1	6	1	4	1	3	1	4	1	4	1	4
9	9	4	5	1	5	1	4	1	3	1	3	2	3	1	6	1	3	4	3	1	2	3	4	1	4
10	10	2	3	3	5	2	5	2	4	3	4	1	2	5	7	2	4	1	4	1	5	3	1	2	1

3.11. Analysis approaches

The counting approach and the modelling one are two methods for analyzing answers to BWS inquiries. They are introduced in the following subsections.

Tab. 3

Data preparation for modelling

	ID	Q	PAIR	BEST	WORST	RES.B	RES.W	RES	Cost
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
1	1	1	1	2	5	8	9	FALSE	0
2	1	1	2	2	7	8	9	FALSE	0
3	1	1	3	2	8	8	9	FALSE	0
4	1	1	4	2	9	8	9	FALSE	0
5	1	1	5	5	2	8	9	FALSE	0
6	1	1	6	5	7	8	9	FALSE	0
7	1	1	7	5	8	8	9	FALSE	0
8	1	1	8	5	9	8	9	FALSE	0
9	1	1	9	7	2	8	9	FALSE	0
10	1	1	10	7	5	8	9	FALSE	0
11	1	1	11	7	8	8	9	FALSE	0
12	1	1	12	7	9	8	9	FALSE	0
13	1	1	13	8	2	8	9	FALSE	0
14	1	1	14	8	5	8	9	FALSE	0
15	1	1	15	8	8	8	9	FALSE	0

16	1	1	16	8	9	8	9	TRUE	0
17	1	1	17	9	2	8	9	FALSE	0
18	1	1	18	9	5	8	9	FALSE	0
19	1	1	19	9	7	8	9	FALSE	0
20	1	1	20	9	8	8	9	FALSE	0
	The respondent's identification number.	Sequential identifier for BWS questions, commencing at number 1.	For each question is the sequential identifier of possible pairs of best /worst attributes	Item number in possible pairs of best-worst attributes in each question, where the attribute is considered the best	Item number in possible pairs of best-worst attributes in each question, where the attribute is considered worst	Item number that was chosen as the best by the respondents	Item number that was chosen as the worst by the respondents	response to a BWS question: if a pair of best and worst items is selected by respondents, it is marked as TRUE, otherwise it is marked as FALSE.	
Convenience	Safety against risks	Security and confidence	Honoring the customer	health cares	Being fast	Accessibility	Flexibility	Dependence on technology	STR
(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)
1	0	0	-1	0	0	0	0	0	101
1	0	0	0	0	-1	0	0	0	101
1	0	0	0	0	0	-1	0	0	101
1	0	0	0	0	0	0	-1	0	101
-1	0	0	1	0	0	0	0	0	101
0	0	0	1	0	-1	0	0	0	101
0	0	0	1	0	0	-1	0	0	101
0	0	0	1	0	0	0	-1	0	101
-1	0	0	0	0	1	0	0	0	101
0	0	0	-1	0	1	0	0	0	101
0	0	0	0	0	1	-1	0	0	101
0	0	0	0	0	1	0	-1	0	101
-1	0	0	0	0	0	1	0	0	101
0	0	0	-1	0	0	1	0	0	101
0	0	0	0	0	-1	1	0	0	101
0	0	0	0	0	0	1	-1	0	101
-1	0	0	0	0	0	0	1	0	101
0	0	0	-1	0	0	0	1	0	101
0	0	0	0	0	-1	0	1	0	101
0	0	0	0	0	0	-1	1	0	101
									a categorical variable that identifies any combination of respondent and question

3.11.1. Counting approach

The approach involves computing the frequency with which item *i* is selected as the best (*Bin*), or the worst (*Win*) among all the questions asked to participant n; that is, to obtain the utility score, we can use the frequency of the best-worst choices, which is the total number of times that an alternative is chosen as the best or the worst. These functions show the perceived utility of that attribute and the sensitivity of the respondent's perception and preferences to changes in the attributes.

The scores can be classified into two main groups: disaggregated scores, which pertain to the individual level, and aggregated scores, which pertain to the total level. The computation details of these scores are presented in Tab. 4. It is deductible from the table that the disaggregated standardized BW score SBW_{in} falls within the range of -1 to +1 because the minimum and maximum values of $BWin$ are -r and +r when respondent n selects item i as the worst and best among all questions containing item i, respectively. $BWin$ equals zero if respondent n chooses item *i* as both the best and the worst equally often, or if respondent n does not choose item *i* as either the best or the worst. The value of $SSQBWi$ provides with an understanding of the relative significance of various items. For instance, values of 0.5 and 0.24 for items *i* and *j*, respectively, indicate that item i is nearly two times more important than item *j*.

Tab. 4

Different scores of the counting approach

Disaggregated scores	Aggregated scores
$BW_{in} = B_{in} - W_{in}$ (4) $SBW_{in} = \frac{BW_{in}}{r}$ (5)	$BW_i = B_i - W_i, (B_i = \sum_n B_{in}, W_i = \sum_n W_{in})$ (6) $SBW_i = \frac{BW_i}{N.r}$ (7) $SQBW_i = \sqrt{\frac{B_i}{W_i}}$ (8) $SSQBW_i = \frac{SQBW_i}{\max(SQBW_i)}$ (9)
r: Frequency of item i in all questions	N: Number of people who responded to the survey

3.11.2. Modelling approach

The method involves the use of discrete choice models to scrutinize the replies. The details of the method have been presented in the following studies, and the interested reader may refer to those works. Assume respondents choose item i as the best and item j as the worst based on their particular utilities (v). The probability of this selection is expressed as the following CL model:

$$P_r(i,j) = \frac{\exp(V_i - V_j)}{\sum_{k=1}^{m} \sum_{l=1, l\neq k}^{m} \exp(V_k - V_l)} \qquad (10)$$

In order to calculate the share of preference for a specific item i (SP_i), the estimated utility coefficients are converted using the CL model choice rule.

$$SP_i = \frac{\exp(V_i)}{\sum_{j=1}^{m} \exp(V_j)} \tag{11}$$

The clogit() function in the survival package can be utilized to conduct an analysis on responses to BWS questions in CL model. To analyze BWS questions where respondents evaluate j items, the model formula is usually structured in the following way:

$$RES \sim ITEM1 + ITEM2 + ... + ITEMj\text{-}1 + strata(STR) \tag{12}$$

where the state variable, *ITEMk*, is associated with the potential best and worst item pairs.

When item *k* is considered as the best item in a given pair, *ITEMk* takes a value of 1, while it takes a value of -1 if item *k* is considered as the worst item in a given pair. When item *k* is not part of any potential best and worst item pairs, *ITEMk* takes a value of 0. The variable *ITEMj* (*j*-th item), has been left out of the equation because its coefficient should be set to zero to establish a reference point. *strata(STR)* is utilized to distinguish each respondent and *BWS* question combination. *RES* and *STR* have been defined earlier [16].

4. FINDINGS

4.1. Counting approach

The results presented in Fig. 4. and Fig. 5. are obtained based on the counting approach for the disaggregated and aggregated scores, respectively. The attributes of safety against risks, security and confidence, being fast, accessibility, and flexibility (in terms of time and choice of intermediary destination, etc.) have positive *BW* standard scores. It means that these attributes are more likely to be chosen as the most important than the least important, and the other attributes are conversely more likely to be chosen as the least important.

Summary of disaggregated best-worst scores:

	meanB	meanW	meanBW	mean.stdBW	stdev.stdBW
cost	1.62	2.02	-0.40	-0.066667	0.6620
Convenience	0.95	1.35	-0.40	-0.066667	0.3871
Safety against risks	1.20	0.99	0.21	0.035000	0.3916
Security and confidence	2.41	0.48	1.93	0.321667	0.4710
Honoring the customer	0.50	1.15	-0.65	-0.108333	0.3065
health care	0.44	1.56	-1.12	-0.186667	0.3966
To be fast	1.16	1.12	0.04	0.006667	0.4027
accessibility	1.75	0.50	1.25	0.208333	0.3395
flexibility	1.32	1.04	0.28	0.046667	0.4451
Dependence on technology	0.46	1.60	-1.14	-0.190000	0.3776

Fig. 4. The results of the disaggregated scores (at the individual level)

Aggregated best-worst scores:

	B	W	BW	stdBW	sqrtBW	std.sqrtBW
cost	162	202	-40	-0.066667	0.8955	0.3997
Convenience	95	135	-40	-0.066667	0.8389	0.3744
Safety against risks	120	99	21	0.035000	1.1010	0.4913
Security and confidence	241	48	193	0.321667	2.2407	1.0000
Honoring the customer	50	115	-65	-0.108333	0.6594	0.2943
health care	44	156	-112	-0.186667	0.5311	0.2370
To be fast	116	112	4	0.006667	1.0177	0.4542
accessibility	175	50	125	0.208333	1.8708	0.8349
flexibility	132	104	28	0.046667	1.1266	0.5028
Dependence on technology	46	160	-114	-0.190000	0.5362	0.2393

Fig. 5. The results of aggregated scores (at the total level)

Comparing *std.sqrt.BW* (aggregated) values shows that the most important roles belong to security and confidence (1.0000), and accessibility (0.8349), respectively. These attributes are approximately 4.2 and 3.5 times more significant than the least attribute of compliance with health cares and social distance with the value of *std.sqrt.BW* (0.2370), respectively. The order of attributes using the counting approach is as follows:

Security and confidence
Accessibility
Flexibility
Safety against risks
Being fast
Cost
Convenience
Honoring the customer
Dependence on technology (cell phone and Internet)
Compliance with health cares and social distancing

4.2. Modelling approach

The results of the CL model based on the data set created with the assumption that the coefficient of *ITEM8* (accessibility) is normalized to zero are presented in Fig. 6.

	coef	exp(coef)	se(coef)	z	p
ITEM1	-0.69930	0.49693	0.09107	-7.678	1.61e-14
ITEM2	-0.65329	0.52033	0.09084	-7.192	6.41e-13
ITEM3	-0.41798	0.65838	0.09060	-4.613	3.96e-06
ITEM4	0.28131	1.32487	0.08996	3.127	0.00177
ITEM5	-0.79012	0.45379	0.09121	-8.663	< 2e-16
ITEM6	-0.98433	0.37369	0.09281	-10.605	< 2e-16
ITEM7	-0.50575	0.60305	0.09199	-5.498	3.85e-08
ITEM9	-0.40822	0.66483	0.09126	-4.473	7.72e-06
ITEM10	-0.96129	0.38240	0.09214	-10.433	< 2e-16

Likelihood ratio test=346.6 on 9 df, p=< 2.2e-16

Fig. 6. The results of the modelling approach

The column p value indicates that all attributes are significantly different from zero at the 1% level. Since the coefficient of *ITEM8* is normalized to zero, the other coefficients show the difference in value from the coefficient of *ITEM8*. Therefore, since the coefficient of *ITEM4* is positive, while the coefficients of the rest of the attributes are negative, it is concluded that *ITEM4* is more important than *ITEM8*, and the rest are less important than *ITEM8*. The comparison of the estimated coefficients of the CL model with the available standardized *BW* (*stdBW*) score is shown in Fig. 7.

	clogit	stdBW
cost	-0.6993024	-0.066666667
Convenience	-0.6532857	-0.066666667
Safety against risks	-0.4179804	0.035000000
Security and confidence	0.2813107	0.321666667
Honoring the customer	-0.7901241	-0.108333333
health care	-0.9843269	-0.186666667
To be fast	-0.5057480	0.006666667
accessibility	0.0000000	0.208333333
flexibility	-0.4082214	0.046666667
Dependence on technology	-0.9612943	-0.190000000

Fig. 7. Comparison of the estimated coefficients of the CL model with the standardized BW score (stdBW)

Fig. 8 and Fig. 9 show the relationship between the two vectors clogit and stdBW. As expected, the correlation between the two vectors is significant. Share of preference is obtained cumulatively using the addmargins function (Fig. 10). It is an easy measure to interpret. For example, the most important attributes of security and confidence (0.204) and accessibility (0.154) are approximately 3.5 and 2.7 times more important than the lowest attribute of compliance with health cares and social distancing (0.058), respectively.

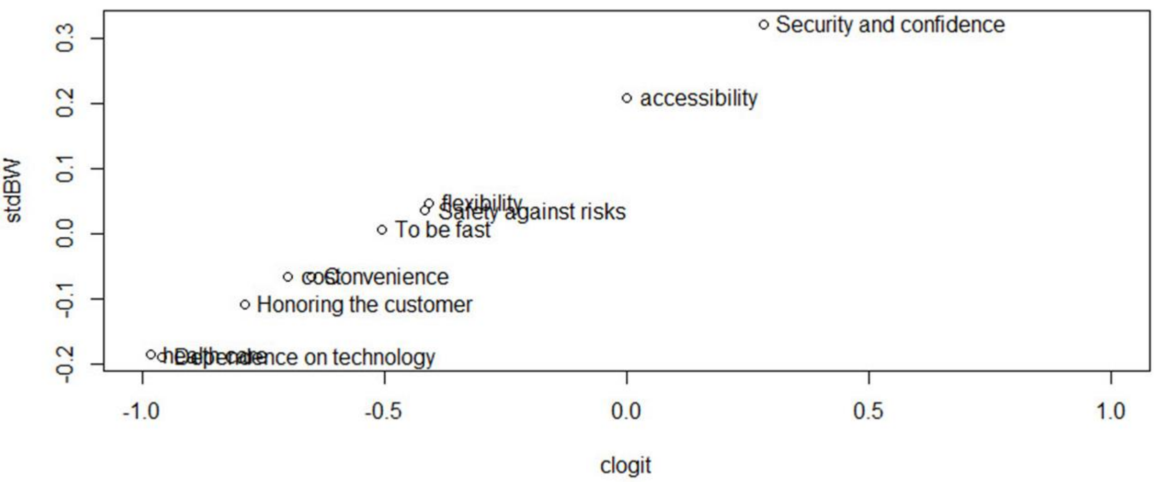

Fig. 8. The relationship between two vectors clogit and stdBW

The order of attributes based on the modelling approach and using the shares of preference is as follows:

Security and confidence
Accessibility
Flexibility
Safety against risks
Being fast
Convenience
Cost
Honoring the customer
Dependence on technology (cell phone and Internet)
Compliance with health care and social distancing

	clogit	stdBW
clogit	1.0000000	0.9993364
stdBW	0.9993364	1.0000000

Fig. 9. Correlation between two vectors clogit and stdBW

	shares
cost	0.07670751
Convenience	0.08031982
Safety against risks	0.10162826
Security and confidence	0.20450915
Honoring the customer	0.07004780
health care	0.05768373
To be fast	0.09308882
accessibility	0.15436224
flexibility	0.10262491
Dependence on technology	0.05902776
Sum	1.00000000

Fig. 10. Shares of preferences of attributes

5. CONCLUSION

Taxi-hailing attributes can be ranked using the BWS-Case 1. Modelling can be done by using the counting approach based on the number of times (frequency) that attribute i is chosen as the best (*Bin*) or worst (*Win*) alternative among all questions of the n respondents or performed by using the conditional logit model in the modelling approach. As can be seen in Tab. 5 the results obtained from the two methods are very similar, and in this study, among the ten attributes examined for Taxi-hailing, there was a difference only in the attributes of the sixth rank and the seventh rank, where the compared values were very close to each other.

It can be seen in Fig. 11 that the attributes of security and confidence, accessibility, flexibility (in terms of time and choice of intermediary destination, etc.) and safety against the risks are above the mean line, and the rest of the attributes are below. Therefore, it is suggested to define levels for these attributes in future studies and to conduct a more detailed study on these attributes using the BWS-Cases 2 and 3.

Tab. 5

Ranking comparison of the counting and modelling approaches

Rank	Counting approach	Modeling approach
1	Security and confidence	Security and confidence
2	Accessibility	Accessibility
3	Flexibility	Flexibility
4	Safety against risks	Safety against risks
5	Being fast	Being fast
6	Cost	Convenience
7	Convenience	Cost
8	Honoring the customer	Honoring the customer
9	Dependence on technology (cell phone and Internet)	Dependence on technology (cell phone and Internet)
10	Compliance with health care and social distancing	Compliance with health care and social distancing

Also, it can be concluded that among the attributes of the Taxi-hailing, mental and spiritual attributes such as security and confidence, and safety against risks that cause mental peace, as well as the attributes of accessibility and flexibility (in terms of time and choice of intermediary destination, etc.) that provide comfort to passengers, are more important than the attributes of being fast, cost, convenience, honoring the customer, dependence on technology (cell phone and Internet) and compliance with health cares and social distancing, which mostly go back to material attributes and physical health and well-being.

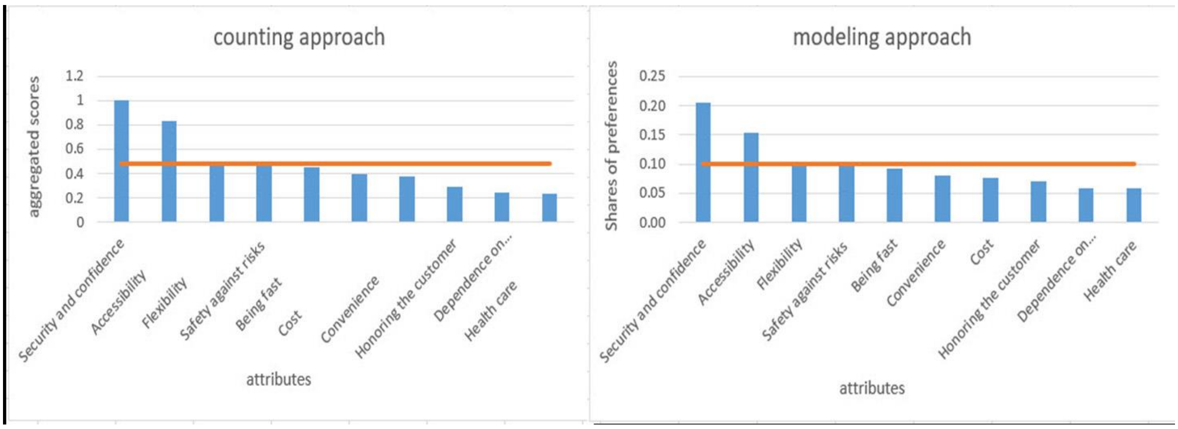

Fig. 11. Scores of attributes in counting approach and modelling approach and comparison with a mean line

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