Traffic & Transportation

Evaluation of Stated Preference Surveys with Statistical Methods

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Original Scientific Paper
Submitted: 22 Mar. 2023
Accepted: 11 July 2023

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Publisher:
Faculty of Transport and Traffic Sciences, University of Zagreb

ABSTRACT

In this paper, the author investigated the stated preference survey in transport modelling. The research was conducted to ensure that the best fractional orthogonal design of stated preference paired comparison survey would not increase the error or uncertainty in transport-related decision modelling. The research was conducted based on artificial Monte Carlo simulated respondents, and the results were assessed with standard mathematical-statistical tools. Although the assessment should have resulted in 0% errors, according to our 2,000 sample, a minor 5% of errors occurred. The problem to be investigated in this paper is that the best-designed survey could have some errors.

KEYWORDS

stated preference survey; willingness to pay; monetary value of travel time.

1. INTRODUCTION

A stated preference survey is used in economics research and social science to study consumers' behaviour and preferences by asking them about their choices [1]. This method could map preferences for certain goods, services or attributes. In a stated preference survey, participants are faced with several hypothetical choices and are asked to decide. This method differs from an actual preference survey, in which individuals are observed making real-life choices, as in stated preference surveys, the choices are only hypothetical [2]. In this paper, the author investigated the pairwise comparison stated preference survey. Pairwise comparison generally is any process of comparing entities in pairs to judge which of each entity is preferred or has a greater amount of some quantitative property or whether or not the two entities are identical [3]. The pairwise comparison method studies preferences, attitudes, voting systems, social choice, public choice, requirements engineering and multiagent AI systems. It is often referred to as paired comparison. Prominent psychometrician L. L. Thurstone first introduced a scientific approach to using pairwise comparisons for measurement in 1927, which he referred to as the law of comparative judgment. Thurstone linked this approach to the psychophysical theory that Ernst Heinrich Weber and Gustav Fechner developed. Thurstone demonstrated that using an interval-type scale, the method could order items along a dimension such as preference or importance [4]. Ernst Zermelo (1928) [5] first described a model for pairwise comparisons for chess ranking in incomplete tournaments, which serves as the basis (even though not credited for a while) for methods such as the Elo rating system and is equivalent to the Bradley-Terry model that was proposed in 1952 [6].

In this paper, the author investigated the fractional orthogonal design of a stated preference paired comparison survey to estimate the monetary value of travel time savings [7]. Orthogonality among the attributes allows estimating the main effects of one variable on choice independently of the effects that the other variables may have. For instance, the passenger car versus bus mode choice travel time difference and travel cost difference could be investigated [8]. If the choices always have the same level for the travel time difference and travel cost difference, it means total collinearity between the two vectors. Estimating the main effect of each of these variables on choice would not be possible. While the fractional factorial approach can significantly reduce the questions needed for a stated preference exercise, it typically ignores some or all interaction effects. Stated preference surveys use willingness-to-pay approaches for particular goods or services to estimate their perceived monetary value [9] in order to analyse the effects of different attributes or factors on consumer behaviour. They are also commonly used to evaluate the potential impact of new products or services or to understand consumer preferences in the context of public policy decisions, such as assessing environmental impacts.

The monetary value of travel time saving refers to the amount of money individuals are willing to pay to reduce the time they spend travelling. The economic value estimates that individuals place on the time they save due to a more efficient or quicker transportation option. The monetary value of travel time saving can be estimated through various methods, including stated preference surveys, revealed preference studies or models that estimate the trade-off between time and money. In stated preference surveys, individuals are asked to state their preferences for travel scenarios, including travel times and costs. In revealed preference studies, individuals' travel behaviour is observed and analysed to determine their value on travel time savings. The monetary value of travel time can vary depending on several factors: income, the purpose of the trip, the availability of alternative modes of transportation and the time of day. It is an essential consideration in the planning and designing of transportation systems and infrastructure, as it can help policymakers determine the potential benefits and costs of different transportation options and make informed decisions about investment in transportation infrastructure.

The primary aim and research question arises: how can one assess if the stated preference survey is good and the results are reliable? The aim of this study is to develop a comprehensive analysis to assess the effectiveness and reliability of stated preference surveys as a research tool, aiming to enhance the quality and validity of survey results.

2. METHODOLOGY

In economics, utility measures a person's satisfaction with a good or service or benefit from consuming a good or service. It is a subjective concept, as different people may have different preferences and values and therefore derive different levels of utility from the same good or service. The utility can be measured in different ways, such as by asking people to rate their satisfaction with a particular product or service or observing their behaviour when making choices in a marketplace [10]. One common way to measure utility is to use a utility function, which assigns a numerical value to each possible combination of goods and services that a person can consume based on their preferences and the prices of the goods. In general, people will try to maximise their total utility by choosing a combination of goods and services that gives them the most satisfaction with the amount of money they spend. This principle is the basis for many economic theories and models, including consumer theory and utility maximisation. In this article, the following linear utility function has been used based on the random utility theory (*Equation 1*):

$$U = a \cdot P + b \cdot TT + g \cdot CT + d \cdot TR + e \tag{1}$$

where:
a – utility weight parameter of price, sensitivity parameter [11]
P – price of travel [12]
b – utility weight parameter of travel time, sensitivity parameter [13]
TT – time of travel [14]
g – utility weight parameter of crowding, sensitivity parameter [15]
CT – crowdedness of travel, sensitivity parameter [16]
d – utility weight parameter of the number of transfers [17]
TR – number of transfers of travel, sensitivity parameter [18]
e – error term of the utility function.

The author used Monte Carlo simulation to generate the responses based on the parameter model of fractional orthogonal stated preference survey based on the given utility functions [19]. The author has defined a, b, g and d as probability variables with their given probability density, the Monte Carlo process assigned randomly selected values from the given probability density functions to calculate unique personal utility [20]. After that, based on the choice of stated preference surveys, the a', b', g' and d' parameters were determined with logit regression modelling [21]. The article aims to investigate if the probability density functions of a', b', g' and d' could fit the original probability density function of a, b, g and d. The logit expression is well-known in decision theory (*Equation 2*):

$$p(x) = \frac{1}{1 + e^{-x}} \tag{2}$$

where $p(x)$ is the probability of choice based on the utility function x. In order to assess the questionnaire in this paper, the author artificially generated 2,000 respondents to evaluate the validity and reliability. The 2,000 respondents had 2,000 different utility functions, where parameters were given as a probability density function to ensure the randomised effect. Therefore, the main question is if the assessment of survey results gives back the theoretical probability density functions of utility parameters. To understand the problem analytically, the following *Equation 3* needs to be solved:

$$\int_{-\infty}^{\infty} \frac{1}{1 + e^{-x}} dx - \int_{-\infty}^{0} 1 dx = 0 \tag{3}$$

The first part is the theoretical logit model of choice. Meanwhile, the second part is the reverse-engineered decision function. It can be easily seen that both figures cover the same area geometrically (*Figure 1*).

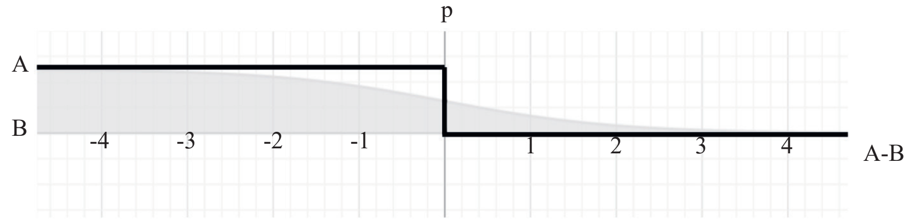


Figure 1 – Visualisation of logit function and stated choice

Therefore, the ideally constructed fractional orthogonal preference survey should give back the distribution parameters of the utility function with no error. As generally accepted, the goodness of the survey was measured by the coefficient of determination (*Equation 4*):

$$R^2 = 1 - \frac{\sum_{i=1}^{n} \left(y_i - \hat{y}_\iota \right)^2}{\sum_{i=1}^{n} \left(y_i - \overline{y_\iota} \right)^2} \tag{4}$$

where:

$\bar{y}_i$ – AI-generated parameter

$\hat{y}_\iota$ – revealed parameter from regression analysis

y_ι– arithmetic average of AI-generated parameters.

Several other factors can be used to assess the goodness of a stated preference survey.

Validity. The validity of a stated preference survey refers to its ability to accurately measure, in this case, the estimated parameters of the utility function. Validity includes the accuracy of the hypothetical scenarios presented to participants and the questions used to elicit their preferences.

Reliability. The reliability of a stated preference survey refers to its ability to produce consistent results when repeated with the same sample of participants. This is important for ensuring that random error or measurement bias does not affect the results.

Representativeness. The representativeness of a stated preference survey refers to its ability to reflect the preferences of the population of interest accurately. Representativeness includes ensuring that the sample of participants is representative of the population and that the hypothetical scenarios presented reflect real-life situations.

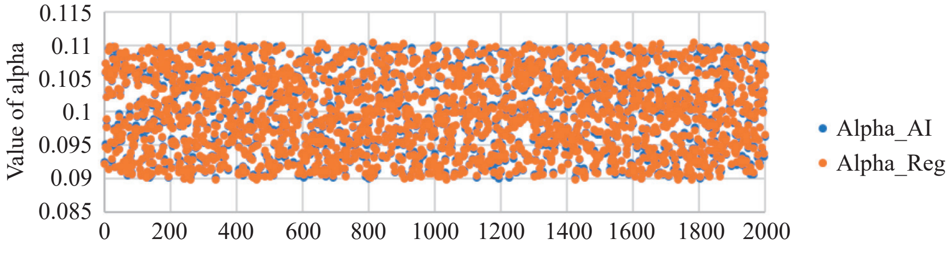
Responsiveness. The responsiveness of a stated preference survey refers to its ability to detect changes in preferences over time or in response to different circumstances. Responsiveness is essential for ensuring that the results remain relevant and up-to-date.

Transparency. The transparency of a stated preference survey refers to the degree to which its methods and results are clearly and openly presented so that they can be easily understood and evaluated.

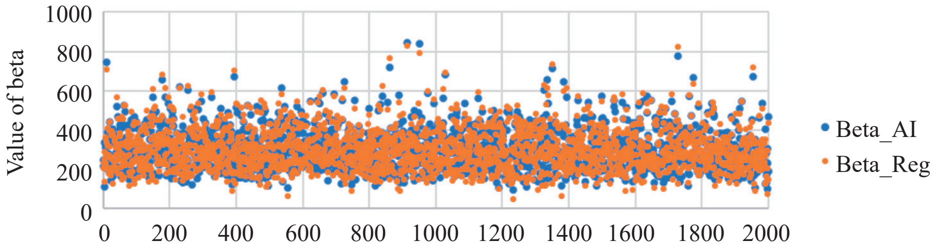
Feasibility. The feasibility of a stated preference survey refers to its practicality and ability to be implemented effectively in terms of cost, time and resources.

3. RESULTS

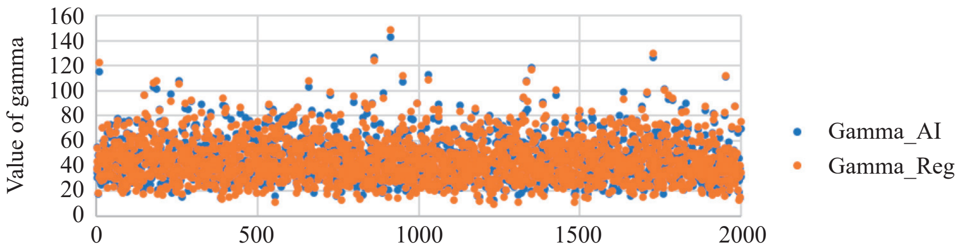
A utility function is a mathematical representation of an individual's preferences over goods, services or outcomes. It quantifies an individual's satisfaction or happiness from consuming a particular combination of goods or services. In economics, the utility function is a mathematical equation that maps inputs (such as the quantities of different goods or services consumed) to a single value representing the individual's total satisfaction or utility. The utility function allows economists to study and analyse consumer behaviour and predict how consumers will respond to price changes or the availability of goods and services. The utility function is usually assumed to satisfy specific properties, such as being non-negative, monotonically increasing and satisfying the law of diminishing marginal utility. These properties reflect the idea that as an individual consumes more of a good, their marginal satisfaction (the additional satisfaction derived from consuming one more unit) will decrease, reflecting the concept of diminishing returns. In practice, the utility function is often estimated using data from surveys or experiments, such as stated preference surveys, which ask individuals to



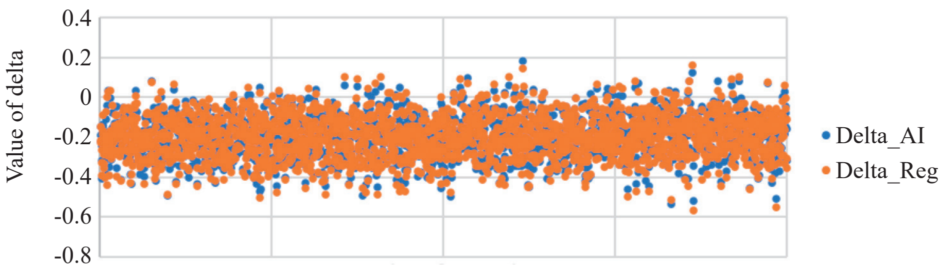
a) Visualisation of alpha parameter



b) Visualisation of beta parameter



c) Visualisation of gamma parameter

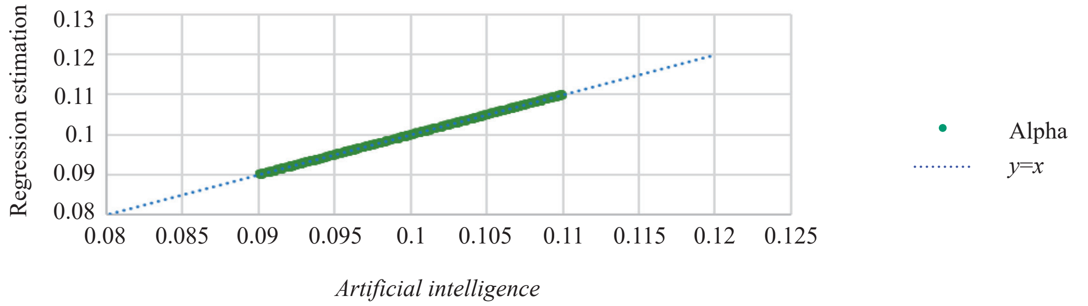


d) Visualisation of delta parameter

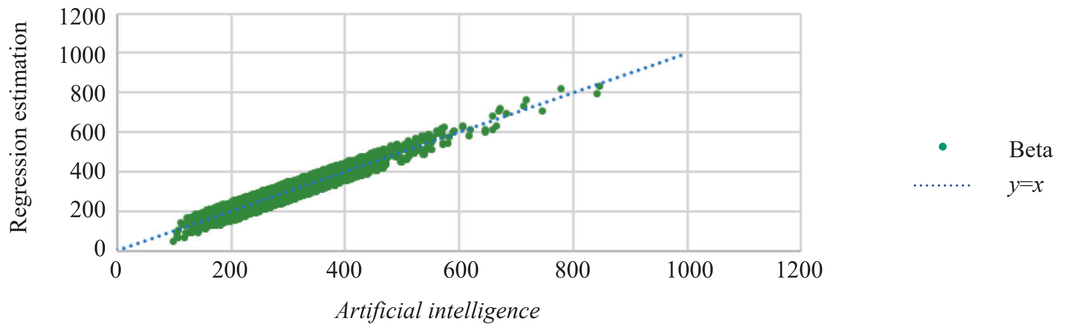
Figure 2 – Visualisation of AI-generated and the revealed parameter from regression analysis

state their preferences for different combinations of goods and services. The resulting utility function can then predict how individuals will allocate their resources given different prices or availability of goods and services.

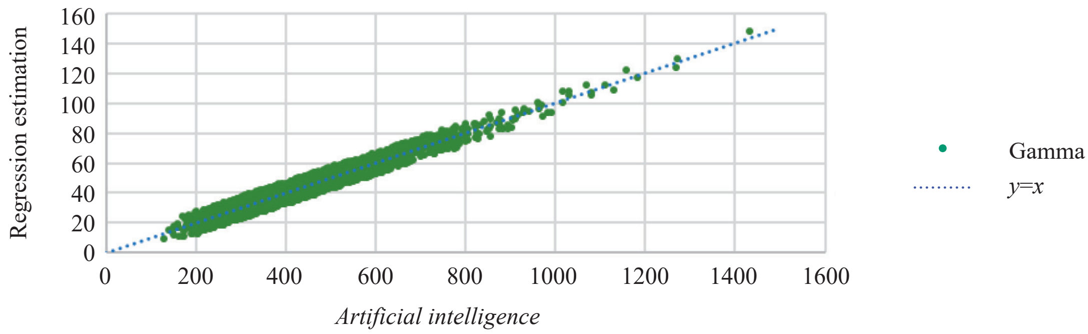
The author has defined *a*, *b*, *g* and *d* as probability variables with their given probability density, the Monte Carlo process calculated unique personal utility functions. After that, based on the choice of stated preference surveys the utility parameters were determined with logit regression modelling. Here one can see the four utility parameters for the 2,000 respondents as created by AI and reverse-engineered by regression (*Figure 2*).



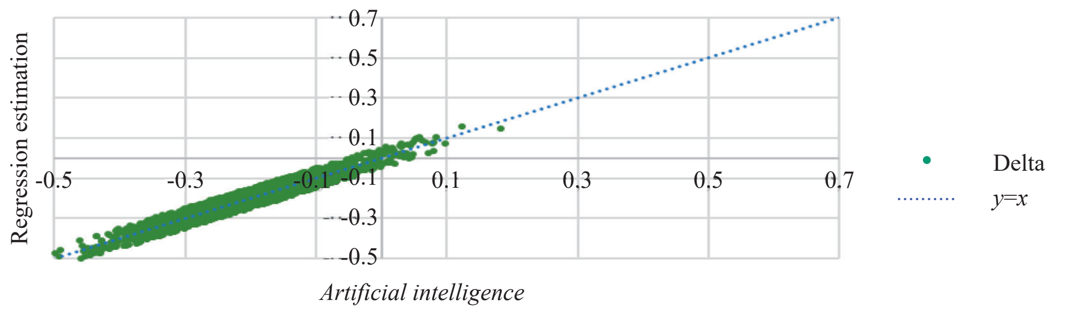
a) Goodness of fit alpha



a) Goodness of fit beta



a) Goodness of fit gamma



a) Goodness of fit delta

Figure 3 – Visualisation of AI-generated and the revealed parameter from regression analysis

By analysing the values of these utility parameters, insights can be gained into respondents' preferences and sensitivities regarding price, travel time, crowding and the number of transfers. The graph serves as a visual representation of these parameters, providing valuable information for transportation planning and decision-making processes.

4. DISCUSSION

This part describes the statistical analysis of AI-generated and the revealed parameter from regression analysis. As shown in *Figure 3*, the revealed parameters fit well to an identical line.

The goodness of the survey was measured by the coefficient of determination (*Table 1*).

Table 1 – Coefficients of determination of parameters

Name of parameter	Alpha	Beta	Gamma	Delta
R^2	0.99	0.91	0.93	0.92

As stated, the reconstruction of the parameters derived from the fractional orthogonal stated preference survey was successful. In addition, the revealed parameters are very close to the artificially generated (*Table 2*).

Table 2 – Descriptive statistic of comparison

Name of parameter	Alpha	Beta	Gamma	Delta
Difference in average	0.004%	-0.447%	-0.152%	-0.122%
The difference in standard deviation	0.002%	-4.175%	-3.364%	-4.395%

In this paper, the author investigated the pairwise fractional orthogonal stated preference survey to determine the monetary value of travel time. Based on the literature, the monetary value of travel time can be estimated based on the sensitivity parameter price and the sensitivity parameter of travel time (*Equation 5*).

$$WTP = \frac{\alpha}{\beta} \tag{5}$$

5. CONCLUSION

When conducting research, there is always a considerable risk if fractional orthogonal stated preference surveys can appropriately measure the investigated process. Are the survey results valid and can they be trusted? What is the limitation of such surveys?

$$\Delta WTP = \frac{\frac{\alpha}{\beta}}{\frac{\alpha'}{\beta'}} \tag{6}$$

The survey proved to be good and the aggregated monetary value of travel time only changed up to 0.5% (*Equation 6*). The proposed process can easily be transferred to any fractional orthogonal stated preference survey if the theoretical probability density function of utility sensitivity parameters is well-known.

ACKNOWLEDGEMENT

The research was supported by OTKA-K20-134760-Heterogeneity in user preferences and its impact on transport project appraisal supervised by Adam Torok. This work was supported by Daniel Tordai, PhD student at Budapest University of Technology and Economics, Department of Transport Technology and Economics.

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Sipos Tibor

Feltárt preferencia alapú kérdőív statisztikai elemzése

Absztrakt

A szerző a közlekedésmodellezésben alkalmazott feltárt preferencia alapó felmérés elemzési lehetőséeit vizsgálta. A kutató célja célja biztosítani, hogy az ortogonális tervezésű kérdőívekben ne növelje a hiba vagy bizonytalanság mértékét a közlekedéssel kapcsolatos döntésmodellezésben. A kutatást mesterséges Monte Carlo szimuláción alapuló válaszadókon végezték, és az eredményeket standard matematikai-statisztikai eszközökkel értékelték ki. Bár az értékelésnek 0% hibát kellett volna eredményeznie, a 2000 minta alapján 3% hiba jelentkezett. A tanulmányban azonosított probléma, hogy a legjobban tervezett felmérés is tartalmazhat hibákat.

Kulcsszavak

feltárt preerncia; fizetési hajlandóság; utazási idő veszteségértéke.