Conjoint analysis based on Thurstone judgement comparison model in the optimization of banking products

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Abstract

Conjoint measurement, as well as conjoint analysis, are statistical methods based on the theoretical frame of axiomatic conjoint measurement. The former concept is widely used in fundamental measurement of subject × object dominance structures (e.g. as IRT and Rasch measurement models), whereas the latest one can be used as a model belonging to a family of object x object dominance structures in both compositional (i.e. Thurestone case III and V), as well as in decompositional approach (classical conjoint experiments and BTL/alpha simulation) preference measurement models. These two traditions are rarely combined in one measurement model and research design that integrates subject × object × object measurement (experiment). The main goal of this paper is to build and to check the goodness of fit of *conjoint* model associated with the use of the latent preferences measurement of banking products based on the theory of comparative assessment Thurstone. Specific objectives include: 1. construction and Evaluation of the Thurstone III and V model fit, as well as Takane-Thurstone model based on confirmatory factor analysis for pair-comparison scale, and 2. application of the estimated continuous product preferences for building a *conjoint* model. The partial utilities will be used to optimize banking products, as well as comparison of models will be presented.

Keywords: *conjoint analysis, Thurstone measurement model, banking products*

JEL Classification: C88, C92

1. Introduction

Conjoint measurement, as well as conjoint analysis, are statistical methods based on the theoretical frame of axiomatic conjoint measurement. The former concept is widely used in fundamental measurement of subject × object dominance structures (e.g. as IRT and Rasch measurement models), whereas the latest one can be used as a model belonging to a family of object x object dominance structures in both compositional (i.e. Thurestone case III and V), as well as in decompositional approach (classical conjoint experiments and BTL/alpha simulation) preference measurement models. These two traditions are rarely combined in one

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measurement model and research design that integrates subject × object × object measurement (experiment).

In this paper we build and to check the goodness of fit of conjoint model associated with the use of the latent preferences measurement of banking products based on the theory of comparative assessment Thurstone. Specific objectives include construction and evaluation of the Thurstone III and V model fit, as well as Takane-Thurstone model based on confirmatory factor analysis for pair-comparison scale, and application of the estimated continuous product preferences for building a conjoint model.

2. Preference measurement methods and conjoint analysis

Determining consumer preferences is still one of the most important topics in marketing research. Not surprisingly, numerous approaches have been developed for this task. Preference measurement methods are: revealed preferences (e.g. historical data analysis) and stated preference (e.g. compositional methods, decompositional methods and mixed methods). Conjoint analysis belongs to the group of decompositional methods, next to discrete choice methods. Conjoint analysis is a powerful market research technique that measures how people make decisions based on certain features of a product or service. The method originated in mathematical psychology and was developed since mid–sixties also by researchers in marketing and business. Conjoint analysis is a statistical method for finding out how consumers make trade–offs and choose among competing products or services. It is also used to predict or simulate consumers` choices for future products or services (Sagan, 2013). The main aim of the conjoint analysis is to estimate part-worth utilities for attribute levels. Part–worth utilities are estimated for each respondent separately, and as average values for whole sample. Estimated part–worth utilities allow estimating: total utilities of profile for all respondents, average total utilities in the sample, average attribute importance, and average total utilities in the segments (clusters) of respondents. Conjoint analysis model can be estimated at individual level (number of models is equal to the number of respondents), as well as at aggregated level (one model for whole sample is estimated). In conjoint analysis attributes or factors are used to describe explanatory variables describing goods or services, attributes levels describe values of attributes and profiles (stimuli, treatments, runs) are variants of goods or services. The most important features of conjoint analysis based on the full profile method are (Vriens, 1992):

- the number of attributes taken into consideration in the research is usually limited to 6,
- profiles presented to respondents to assess are described by using all attributes,

- profiles are generated on the basis of orthogonal factor system,
- profiles generated on the basis of orthogonal systems which are maximally and mutually varied,
- main effects and also the effects of an attribute interaction can be incorporated into the conjoint analysis model,
- all respondents assess the same set of profiles,
- the conjoint analysis model represent so called decomposition approach, which means that on the basis of empirical usages of full profiles, it is possible to assess partial usages of attribute levels,
- different methods of gathering data from original, primitive sources can be used,
- each stage of conjoint analysis procedure is separated (namely: preparing profiles, gathering data, assessing parameters, simulating market shares).

Conjoint analysis will be applied in this paper with the use of R software.

3. IRT models

Item Response Theory (IRT), as an extension of Classical Test Theory (CTT), are psychometric models used in education assessments and testing, that have roots in psychological measurement (Binet and Simon, 1916; Thurstone, 1925; Lawley, 1943; Lord et al., 1968; DeMars, 2010). Crucial work by Lord and Novick (1968) and Birnbaum (1968) has been instrumental in establishing an understanding and acceptance of IRT among psychological measurement practitioners. Rasch (1960) played a huge role in the development a specific class of IRT models and showing a number of their desirable features. From a more statistical point of view, later contributions by Birnbaum (1968) were important. He replaced the normal ogive by the logistic function, introduced additional item parameters to account for guessing on items (which is typical of most educational measurements), derived maximum-likelihood estimators for the model, and showed how to assemble tests from a bank of calibrated items to meet optimal statistical specifications for their application. In response models theory, there are dichotomous items and polytomous models, where test items have a polytomous format when more than two response categories are used to score an item.

IRT is a psychometric theory and family of associated mathematical models that relate latent trait of interest to the probability of responses to items on the assessment. It is very general method, permitting one or more traits, various (testable) model assumptions and the analysis of binary or polytomous data. The mechanism of IRT can be presented most easily in term of a dichotomous model, that is, a model for item with only two response alternatives. The IRT function requires the estimation of two parameters. One is location parameter, which describes where along the trait continuum the function is centered. The second parameter is estimated to give information on of how well an item discriminates among people along the trait continuum and shows how well an item can tell people apart with respect to the amount of a trait that they have. When data is binary, a class of models from Item Response Theory (IRT) is used, such as Rasch model (Bond and Fox, 2015). This model allows to model subject heterogeneity by the specification of corresponding parameters.

4. Research design

The research on banking products and bank account preferences was conducted in Poland. The product analyzed were bank account choices of bank customers. Attributes and levels were:

1. Bank account access via mobile devices ($X1$): (a) yes, (b) no,
2. Bank account commission ($X2$): (a) yes, (b) no,
3. Credit card payment return ($X3$): (a) yes, (b) no,
4. Fee for withdrawal in foreign ATM machines ($X4$): (a) yes, (b) no,
5. Credit card free of charge ($X5$): (a) yes, (b) no.

Profiles were respondents asked to make a choice between 28 pairs of profiles (fractional factorial design prepared with R software). Full factorial design contained 32 profiles, fractional factorial design was 8 profiles (Table 2). For full profile generation we need to load package AlgDesign of R software. Usually full profile design is not used in conjoint analysis due to high number of profiles. When the number of profiles is relatively (up to 16) all profiles can be used. Otherwise partial profile design has to be prepared. Evaluations were applied in package conjoint (Bąk and Bartłomowicz, 2012) and part-worth utilities were estimated. Obtained part-worth utilities were used to calculate attractiveness (total utilities) of individual profile and average attribute importance.

4.1. Measurement models Thurstone III and V

In his paper we present the problem of validation of measurement model in consumers` preferences analysis. The overall preferences of the profiles are measured on interval Likert-type scales or ordinal scales using rank order method or paired – comparison technique. In both cases, the measurement of dependent variable for conjoint analysis is model-free and it is done on ordinal scale. This limits the OLS regression-based conjoint model (instead

MONANOVA should be used for ordinal measurement of overall preferences) and provides no evidence for reliability assessment.

In subsequent research, the ordinal paired-comparison scale is used for obtaining the preference rankings. This method enables to identify the intransitive preferences of the consumers, where the number of comparisons is equal to k = n(n-1)/2, the number of comparison patterns is $p = 2^k$ and the number of intransitive patterns is equal n!.

In order to develop the measurement model for the overall preferences that are measured on paired-comparison scale, the three thurstonian models with latent preferences (as a latent variables) were estimated: 1/ unrestricted model, 2/ thurstonian case III model and thurstonian case V model. In unconstrained model all model parameters are freely estimated, except identification constrains (the mean of last latent variable is fixed to 0, all covariances involving last latent variable is fixed to 0, and variances of the first and last latent variables are fixed to 1):

$$\mu_t = \begin{pmatrix} \mu_1 \\ \mu_2 \\ \mu_3 \\ 0* \end{pmatrix}, \sum_t = \begin{pmatrix} 1* & \sigma_{21} & \sigma_{31} & 0* \\ \sigma_{21} & \sigma_2^2 & \sigma_{32} & 0* \\ \sigma_{31} & \sigma_{32} & \sigma_3^2 & 0* \\ 0* & 0* & 0* & 1* \end{pmatrix}. \tag{1}$$

In model III the means of the last latent variable is fixed to 0, all covariances are fixed to 0, and variance of the last latent variable is fixed to 1:

$$\mu_t = \begin{pmatrix} \mu_1 \\ \mu_2 \\ \mu_3 \\ 0* \end{pmatrix}, \sum_t = \begin{pmatrix} \sigma_1^2 & 0 & 0 & 0 \\ 0 & \sigma_2^2 & 0 & 0 \\ 0 & 0 & \sigma_3^2 & 0 \\ 0 & 0 & 0 & 1* \end{pmatrix}. \tag{2}$$

In model V the means of the last latent variable is fixed to 0, all covariances are fixed to 0, and variance of all latent variables are standardized and are fixed to 1:

$$\mu_t = \begin{pmatrix} \mu_1 \\ \mu_2 \\ \mu_3 \\ 0* \end{pmatrix}, \sum_t = \begin{pmatrix} 1* & 0 & 0 & 0 \\ 0 & 1* & 0 & 0 \\ 0 & 0 & 1* & 0 \\ 0 & 0 & 0 & 1* \end{pmatrix}. \tag{3}$$

In Thurstone preference models, the parameters (means, variances and covariances) of latent variables were estimated using categorical structural equation modelling on paired comparisons data with means and covariances structures. In measurement models the factor loadings were fixed to 1 (i.e. A–B comparison) or -1 (i.e. B–A comparison) for the particular profiles (A–H) . Thresholds for the categorical indicators of preferences were fixed to 0.

Comparative analysis of the models gave the following AIC (*Akaike Information Criterion*) indicators:

- unrestricted model = 9042.195,
- case III model = 9086.549 and
- case V model = 9295.274.

The AIC criterion shows that the most complex (unrestricted) model seems to be the best one, however the differences between information criteria are not large, and incremental improvement between the best and worse model is to sufficient. Additionally, the correlation between the factor scores of model III and V is relatively high (above 0.85). Taking into account the simplicity criterion the thurstonian model V were selected. The structure of the model and goodness of fit indices are depicted on Fig. 1.

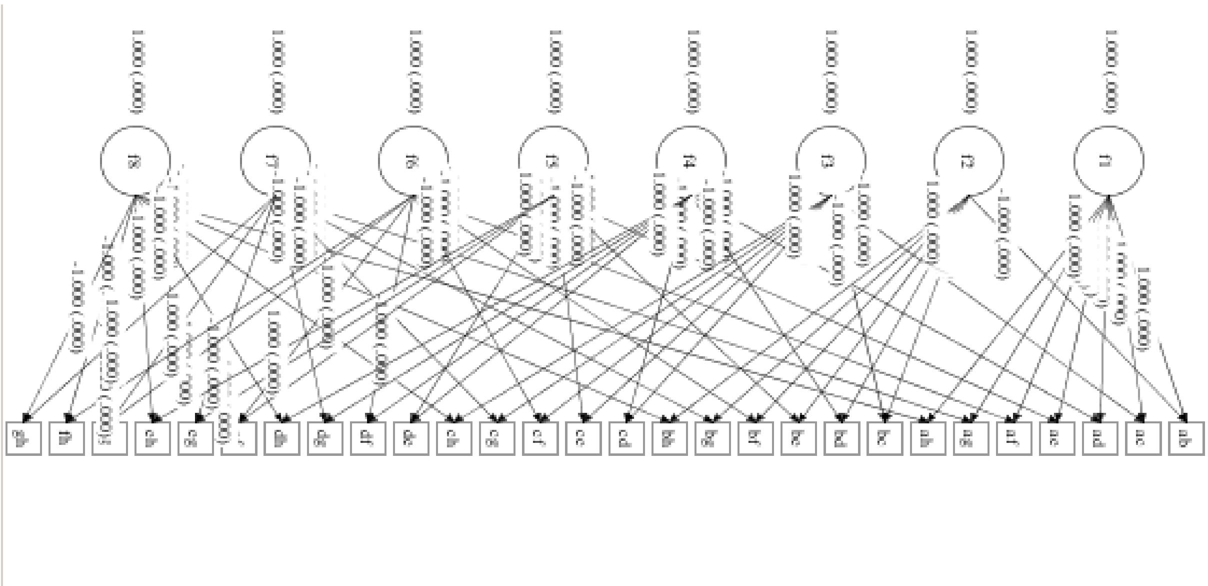

Fig. 1. The structure of Thurstone case V model.

In measurement part of the model, the 28 (8 x 7)/2 pairs are the indicators of latent consumer preferences. The factor loadings are fixed to 1.00 or -1.00 depending on the direction of comparisons. The latent preferences of the 8 profiles are assumed to be independent and all variances of preferences are set to 1.00. In the estimation process, the robust maximum likelihood method (MLR) with probit link function was used. Because the frequency table for the latent class indicator model was too large, the Chi-square test was not computed and only loglikelihood (-4963.795). The estimated factor scores were used as a model-based metric indicators of unobserved overall consumer preferences for conjoint analysis.

4.2. Conjoint analysis

Detailed information on conjoint analysis results is presented in Table 1, where we show part worths utilities of attributes levels for whole sample.

No.	Attribute	Level	Part-worth
1	Bank account access via mobile devices	yes	-0.1286
		no	0.1286
2	Bank account commission	yes	0.0552
		no	-0.0552
3	Credit card payment return	yes	-0.0244
		no	0.0244
4	Fee for withdrawal In foreign ATM machines	yes	-0.029
		no	0.029
5	Credit card fee of charge	yes	-0.0968
		no	0.0968

Table 1. Part worths utilities of attributes levels for whole sample.

Conjoint analysis was conducted and total utilities (ranks) of the profiles were obtained (Table 2). Best profile marked with 1 in respondents' opinion was the 4-th profile: the bank account access via mobile devices, and credit card free of charge, with no bank commission, no credit card payment return, and no fees for withdrawal in foreign ATM machines (Table 2). The worst profile in respondent`s opinion is the 6-th profile: with bank account commission and free for withdrawal in ATM machines, but without bank account access via mobile devices, no credit card payment and no credit card free of charge.

In respondents' opinion choosing bank account the most important attribute was bank account access via mobile devices, bank account commission, credit card free of charge, credit card payment return and finally free withdrawal in foreign ATM machines.

Graphical presentation of attributes importance in conjoint analysis is presented in Fig. 2.

Number of profile	Bank account access via mobile devices	Bank account comission	Credit card payment return	Fee for withdrawal in foreign ATM machines	Credit card free of charge	Total utility (rank)
1	no	no	yes	yes	yes	4
2	yes	yes	no	yes	yes	2
3	no	yes	yes	no	yes	6
4	**yes**	**no**	**no**	**no**	**yes**	**1**
5	yes	no	yes	yes	no	3
6	no	yes	no	yes	no	8
7	yes	yes	yes	no	no	5
8	no	no	no	no	no	7

Table 2. Rank of total utilities of profiles.

Attributes importance in conjoint analysis is presented in Table 3.

Attributes	Attributes importance
Bank account access via mobile devices	22.00
Bank account commission	21.55
Credit card payment return	18.09
Fee for withdrawal in foreign ATM machines	17.27
Credit card fee of charge	21.09

Table 3. Average importance of attributes for whole sample.

Conclusions

The hybrid-conjoint model is promising way to measurement of consumer preferences. Combining Thurstone measurement model with conjoint analysis framework in unified approach helps to measure the overall preferences as latent variables on metric level, control the assumptions of various measurement models compared, and evaluate the reliability of measurement. It allows using all regression-based approaches to conjoint analysis.

The conjoint analysis shows that the most important attribute is bank account access via mobile devices, bank account commission, credit card free of charge, credit card payment return and finally free withdrawal in foreign ATM machines. The most attractive profile was the 4-th profile: the bank account access via mobile devices, and credit card free of charge, with no bank commission, no credit card payment return, and no fees for withdrawal in foreign ATM machines.

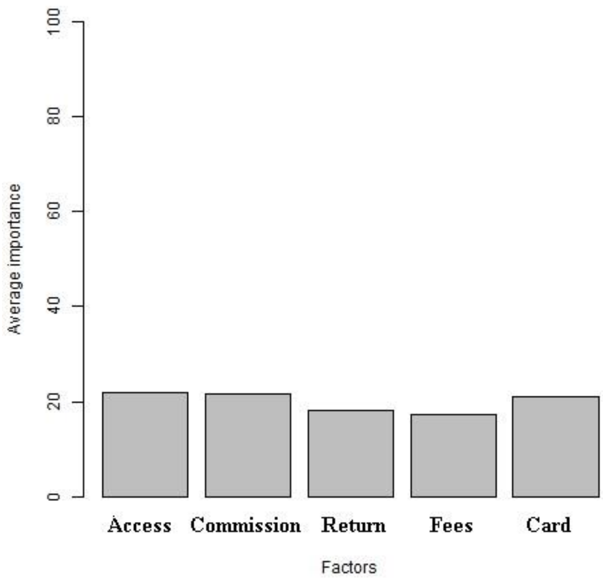

Fig. 2. Attribute importance ranking.

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