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IRT-BASED CONJOINT ANALYSIS IN THE OPTIMIZATION OF BANKING PRODUCTS

CONJOINT ANALYSIS OPARTA NA MODELACH IRT W OPTYMALIZACJI PRODUKTÓW BANKOWYCH

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Summary: Conjoint measurement and analysis have a common underlying psychometric and statistical assumption concerning axioms of additivity and two-way frame of reference in preference measurement. However, whereas the former concept is widely used in the fundamental measurement of subject × object dominance structures as in IRT and Rasch measurement models, the latter is utilized in a broad family of object × object dominance structures in both compositional (i.e. Thurstone case III and V) as well as decompositional (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 [Neubauer 2003]. The aim of the paper is to adopt and compare three types of preference measurement models in the area of banking products in Poland: 1. paired-comparisons and rating scale conjoint experiment, 2. IRT-based conjoint (Rasch and Birnbaum politomous models), 3. compositional Thurstone III/V models [Bockenholt 2006]. Part-worth utilities are used for product optimization and comparison across the estimated models.

Keywords: conjoint measurement, conjoint analysis, IRT models, banking products.

Streszczenie: Zarówno pomiar łączny (*conjoint measurement*), jak i analiza łączna (*conjoint analysis*) oparte są na wspólnym podstawowym, psychometrycznym i statystycznym założeniu dotyczącym addytywności oraz dwukierunkowości układu odniesienia w pomiarze preferencji. Wcześniejsza koncepcja jest szeroko wykorzystywana w podstawowym pomiarze dominacji podmiotu × obiektu (np. modele IRT, modele Rascha). Koncepcja późniejsza wykorzystywana jest w szerszej rodzinie struktur dominacji obiektu × obiektu, zarówno w podejściu kompozycyjnym (model III i V Trurestone'a), jak i w podejściu dekompozycyjnym (tradycyjna *conjoint analysis* i modele symulacyjne BTL/alpha). Te dwie koncepcje są rzadko łączone w jeden model pomiaru w ramach jednego badania (jednego eksperymentu). Celem niniejszego artykułu jest przyjęcie (zastosowanie) i porównanie trzech modeli pomiaru preferencji w obszarach produktów bankowych, jak: 1) eksperymenty *conjoint* wykorzystujące metodę prezentacji profilów parami (*paired-comparisions*) oraz metodę prezentacji profilów na skali ocen (*rating scale*), 2) *conjoint analysis* oparta na IRT (modele Racha i Birnbauma), 3) kompozycyjne modele III/V Thurstone'a [Bockenholt 2006]. Użyteczności cząstkowe zostaną wykorzystane do optymalizacji produktów oraz porównania szacowanych modeli.

Słowa kluczowe: pomiar *conjoint*, *conjoint analysis*, modele IRT, produkty bankowe.

1. 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, decompostional 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 has been 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 (simulate) consumers choices for future products or services [Sagan 2013]. The main aim of 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 the whole sample. Estimated part-worth utilities allow to estimate: 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. A conjoint analysis model can be estimated at individual level (the number of models is equal to the number of respondents), as well as at aggregated level (one model for the 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 the orthogonal factor system,

- profiles generated on the basis of orthogonal systems which are maximally and mutually varied,
- the 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 represents the 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, basic sources can be used,
- each stage of conjoint analysis procedure is separated (namely: preparing profiles, gathering data, assessing parameters, simulating market shares).

2. Item Response Theory models

Item Response Theory (IRT) is an extension of Classical Test Theory (CCT) with roots from psychology and psychological measurement [Binet, Simon 1916; Thurstone 1925]. Crucial work by Lord and Novick [Lord, Novick 1968] and Birnbaum [Birnbaum 1968] was instrumental in establishing an understanding and acceptance of IRT among psychological measurement practitioners. Rasch [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, the later contributions by Birnbaum [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 the 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 the responses are scored in more than two categories.

IRT is a psychometric theory and family of associated mathematical models that relate the latent trait of interest to the probability of responses to items on the assessment. It is a 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 terms of a dichotomous model, that is a model for an item with only two response alternatives. The IRT function requires the estimation of two parameters. One is a location parameter which describes where along the trait continuum the function is centered. The second parameter is estimated to give information on 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 the Rasch model. This model allows to model subject heterogeneity by the specification of corresponding parameters.

3. Thurstone and Rasch measurement models

In conjoint analysis the measurement of overall preferences (as the dependent variable) is usually carried out without taking into account any measurement model. It is usually assumed that the preferences are measured on ordinal scales (for rank orders of the profiles) or metric (for the Likert-type rating scales of the profiles). The Thurstone or Rasch measurement models of profile preferences thus take into account the nature of metric measurement (on a stronger scale) of preferences as a latent variable and allow for the assessment of the measurement error of latent preferences. There are distinctive types of comparative judgements models. An unlimited model does not impose any restrictions in the model structure. Identification constraints consist in establishing one mean for category=0, and setting a variance for the first and the last category=1. The Thurstonian case III model assuming independence of preferences (lacking correlation between preferences). Model III identification constraints consists in setting a mean value for the category=0, and setting all covariances=0 (independence of preferences), and setting a variance for the last category=1. The Thurstonian case V model, assuming the same variance of preferences. Models are structured on the basis of rating scales of preferences including only transitional preferences. Item Response Theory (IRT) is a statistical theory that distinguishes the latent trait (ability) of a participant from the difficulty of a set of item with well-correlated response patterns. Item Response Theory models were formally presented by Lawley [Lawley 1943] who introduced IRT as a measurement theory and later developed by Rasch [Rasch 1960] to measure the ability and to devise tests for the military. Samejima [Samejima 1969] developed graded response models in IRT for polytomous IRT models that deal with Likert-scale data and other tests with ordered multiple response option for each item [De Mars 2010]. IRT models are often referred to as latent trait models. One IRT model is the Rasch model for dichotomous data, often regarded as an item response theory (IRT) model with one item parameter. However, rather than being a particular IRT model, proponents of the model regard it as a model that possesses a property which distinguishes it from other IRT models [Bond, Fox 2001]. Specifically, the defining property of Rasch models is their formal or mathematical embodiment of the principle of invariant comparison. The Rasch models were developed for the analysis of data from mental tests. Although the Rasch models have been in existence for such a long time, their use was limited to dichotomous items. This is too restrictive for practical testing purposes and researchers should focus on extended Rasch models. The basic Rasch model is used to separate the ability of test takers and the quality of the test.

4. Research design

4.1. Data description

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 (*X*1): (a) yes, (b) no,
2. Bank account commission (*X*2): (a) yes, (b) no,
3. Credit card payment return (*X*3): (a) yes, (b) no,
4. Fee for withdrawal in foreign ATM machines (*X*4): (a) yes, (b) no,
5. Credit card free of charge (*X*5): (a) yes, (b) no.

Profiles were respondents asked to make a choice between 28 pairs of profiles (fractional factorial design prepared with R software). The full factorial design contained 32 profiles, the fractional factorial design was 8 profiles (Table 1).

Table 1. Profiles in conjoint analysis

Profile	Bank account access via mobile devices	Bank account commission	Credit payment return	Fee for withdrawal in foreign ATM machines	Credit card charge fee
1	no	no	yes	yes	yes
2	yes	yes	no	yes	yes
3	no	yes	yes	no	yes
4	yes	no	no	no	yes
5	no	yes	no	yes	no
6	yes	yes	yes	no	no
7	yes	no	yes	no	no
8	no	no	no	no	no

Source: own calculations.

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 the high number of profiles. When the number of profiles is relatively low (up to 16) all profiles can be used, otherwise partial profile design has to be prepared. Evaluations were applied in a conjoint package [Bąk, Bartłomowicz 2012] and part-worth utilities were estimated.

4.2. Measurement models Thurstone V and Rasch

Data-based Thurstonian case V preference scale used the original paired-comparison scale of the profiles preferences. The final preference scale shows the interval distances between the profile preferences (A-H profiles) (Figure 1). The estimated means of latent preferences are the following: factor loadings are fixed to 1 or –1, loglikelihood value = –4626.012, and scaling correction factor for MLR=0.51.

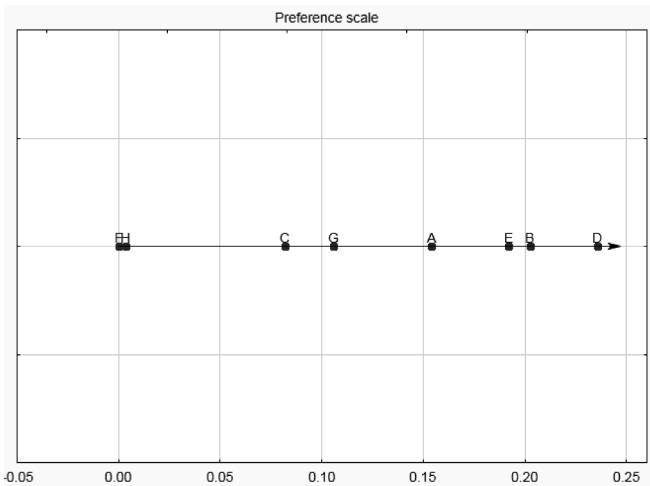

Fig. 1. Final preference scale

Source: own calculations.

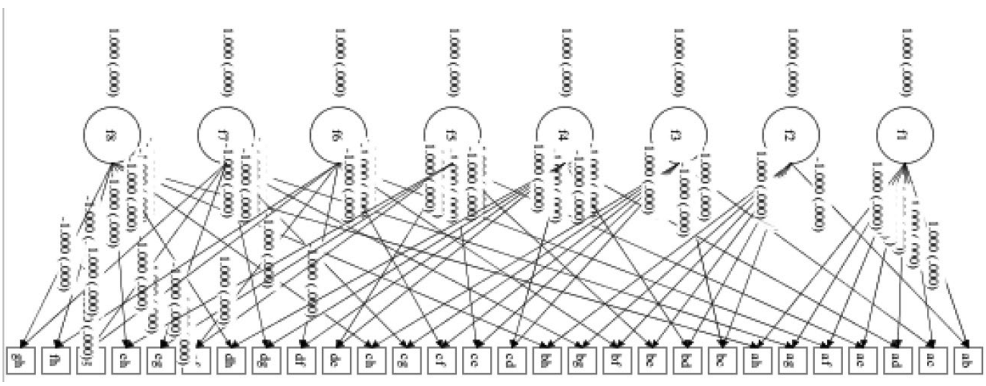

Fig. 2. Thurstone preference model

Source: own calculations.

The Thurstone preference model used a structural equation model on paired comparison data. Factor loadings are fixed to 1 (if A dominates B) or –1 (if B dominates A) for particular items. The model assumes independence of preference formation. Means of latent preference for the profiles are estimated. Thresholds for categorical items are fixed to 0 (Figure 2). The Rasch model of preferences using structural equation model on paired comparison data was built. Factor loadings are fixed to 1 (if A dominates B) or –1 (if B dominates A) for particular items. The model assumes unidimensionality of preferences (estimated as many models as number of profiles). Only positive domination structures are shown on the item characteristic curves graphs. Means of latent preference for the profiles are fixed to 0 .Thresholds for categorical items are estimated. Preference analysis is based on the comparison between appropriate pairs of items, i.e. AC in profile A model with AC in profile C model. All the Rasch models for profile A to H are presented below. The Rasch model for profile A is presented in Figure 3. For this model we get the following estimate of item difficulties: $AB\$1 = -0{:}380$, $AC\$1 = 0{:}118$, $AD\$1 = -0{:}001$, $AE\$1 = 0{:}217$, $AF\$1 = -0{:}219$, $AG\$1 = -0{:}041$, and $AH\$1 = -0{:}120$. Chi–square test of the model fit is 300.22 (120), p=0.000. The Rasch model for profile B is presented in Figure 4. For this model we get the following estimate of item difficulties: $AB\$1 = 0{:}401$, $BC\$1 = -0{:}362$, $BD\$1 = 0{:}259$, $BE\$1 = -0{:}021$, $BF\$1 = -0{:}321$, $BG\$1 = -0{:}548$, and $BH\$1 = -0{:}465$. Chi–square test of the model fit is 211.22 (120), p=0.000. The Rasch model for profile C is presented in Figure 5. For this model we get the following estimate of item difficulties: $AC\$1 = -0{:}112$, $BC\$1 = 0{:}370$, $CD\$1 = 0{:}288$, $CE\$1 = 0{:}088$, $CF\$1 = -0{:}293$, $CG\$1 = 0{:}188$, and $CH\$1 = 0{:}028$. Chi–square test of the model _t is 182.12 (120), p=0.000. The Rasch model for profile D is presented in Figure 6. For this model we get the following estimate of item difficulties: $AD\$1 = 0{:}010$, $BD\$1 = -0{:}257$, $CD\$1 = -0{:}298$, $DE\$1 = -0{:}174$, $DF\$1 = -0{:}319$, $DG\$1 = -0{:}154$, and $DH\$1 = -0{:}487$. Chi–square test of the model fit is 101.21 (120), p=0.89. The Rasch model for profile E is presented in Figure 7. For this model we get the following estimate of item difficulties: $AE\$1 = -0{:}202$, $BE\$1 = 0{:}035$, $CE\$1 = -0{:}083$, $DE\$1 = 0{:}174$, $EF\$1 = -0{:}302$, $EG\$1 = -0{:}322$, and $EH\$1 = -0{:}282$. Chi–square test of the model fit is 189.34 (120), p=0.00.

The Rasch model for profile F is presented in Figure 8. For this model we get the following estimate of item difficulties: $AF\$1 = 0{:}241$, $BF\$1 = 0{:}343$, $CF\$1 = 0{:}302$, $DF\$1 = 0{:}322$, $EF\$1 = 0{:}322$, $FG\$1 = 0{:}261$, and $FH\$1 = 0{:}017$.

Chi-square test of the model fit is 168.14 (120), $p = 0.02$. The Rasch model for profile G is presented in Figure 9. For this model we get the following estimate of item difficulties: $AG\$1 = 0{:}056$, $BG\$1 = 0{:}559$, $CG\$1 = -0{:}182$, $DG\$1 = 0{:}155$, $EG\$1 = 0{:}335$, $FG\$1 = -0{:}242$, and $GH\$1 = -0{:}362$. Chi-square test of the model fit is 234.04 (120), $p = 0.00$. The Rasch model for profile H is presented in Figure 10. For this model we get the following estimate of item difficulties: $AH\$1 = 0{:}120$, $BH\$1 = 0{:}465$, $CH\$1 = -0{:}039$, $DH\$1 = 0{:}465$, $EH\$1 = 0{:}281$, $FH\$1 = -0{:}019$, and $GH\$1 = 0{:}362$. Chi-Square Test of the model fit is 220.4 (120), $p = 0.00$.

To summarize, the Rasch-based measurement model reflects the preference ordering of profiles from the Thurstone analysis and enables to use estimated factor scores as a metric latent variable of banking product preferences for the conjoint model.

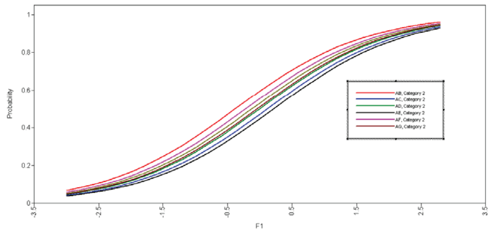

Fig. 3. Rasch model (profile A)

Source: own calculations.

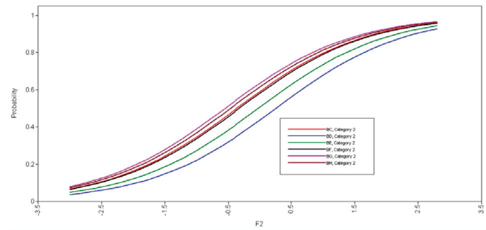

Fig. 4. Rasch model (profile B)

Source: own calculations.

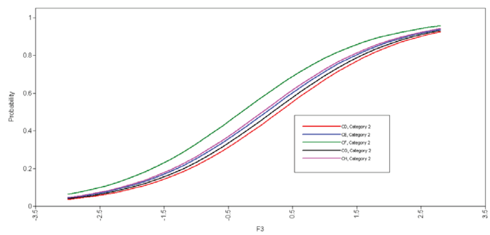

Fig. 5. Rasch model (profile C)

Source: own calculations.

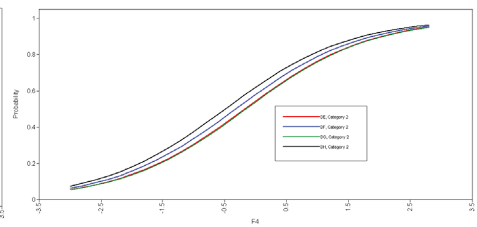

Fig. 6. Rasch model (profile D)

Source: own calculations.

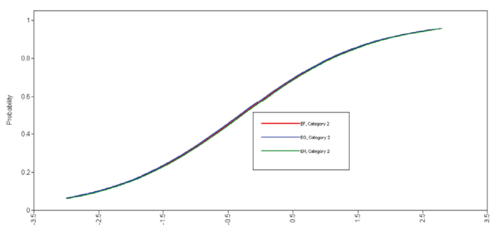

Fig. 7. Rasch model (profile E)

Source: own calculations.

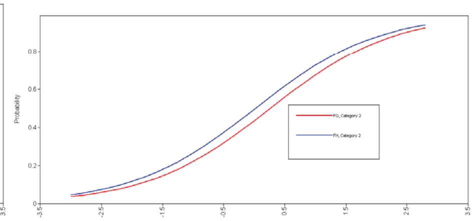

Fig. 8. Rasch model (profile F)

Source: own calculations.

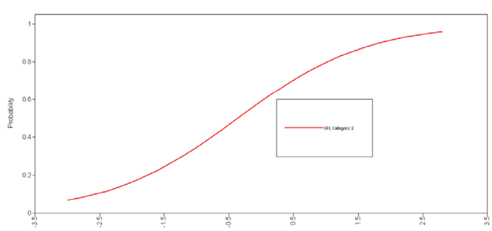

Fig. 9. Rasch model (profile G)

Source: own calculations.

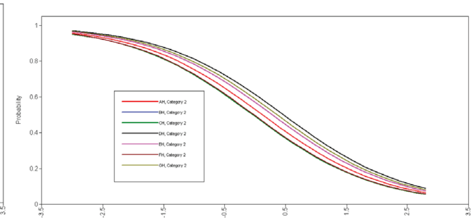

Fig. 10. Rasch model (profile H)

Source: own calculations.

Table 2. Rank of total utilities of profiles

Profile	Bank account access via mobile devices	Bank account commission	Credit payment return	Fee for withdrawal in foreign ATM machines	Credit card charge fee	Rank
1	no	no	yes	yes	yes	8
2	yes	yes	no	yes	yes	2
3	no	yes	yes	no	yes	4
4	yes	no	no	no	yes	6
5	no	yes	no	yes	no	5
6	yes	yes	yes	no	no	3
7	yes	no	yes	no	no	1
8	no	no	no	no	no	7

Source: own calculations.

The importance of attributes are presented in Figure 11.

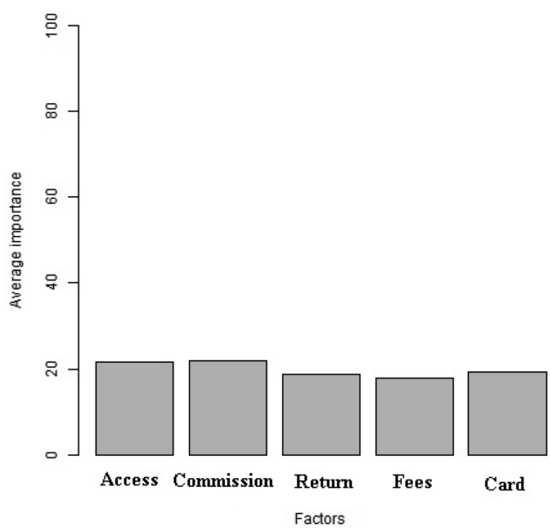

Fig. 11. Attributes importance

Source: own calculations.

4.3. Conjoint analysis of banking products

Conjoint analysis was conducted and total utilities (ranks) of the profiles were obtained. Detailed information on conjoint analysis results is presented in Table 2. The best profile marked with 1 in the respondents` opinion was the 7th profile: the bank account access via mobile devices, with bank commission and credit card payment return, but with no fees for withdrawal in foreign ATM machines and no credit card fees. In respondents` opinion, when choosing a bank account the most important attribute was bank account commission, bank account access via mobile devices, credit card charge fee, credit card payment return, and finally the fee for withdrawal in foreign ATM machines.

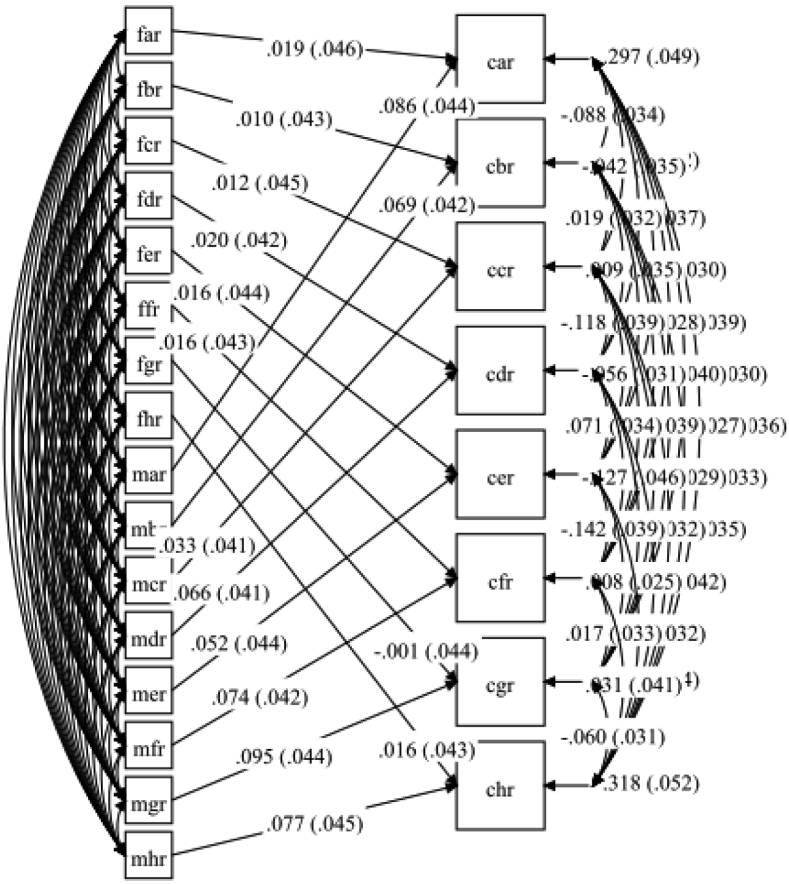

Fig. 12. Preference interdependence model, where: m – mother, f – father, c – child.
The model presents the influence of parents' preferences (mother and father)
on the child's preferences. The results show that mothers play an important role in shaping children preferences with respect to profiles A and G

Source: own calculations.

4.4. Preference interdependence model

Research among family members assumes the interdependence of profiles preferences, due to social interactions and non-independence data, F4 presents the APIM (actor-partner interdependence) model of preference interaction among family members [Kenny, Kashy, Cook 2006]. The model presents the influence of parents' preferences (mother and father) on their children's preferences of banking products. The results show that mother plays an important role in shaping children's preferences with respect to profiles A and G (Figure 4). Chi–Square Test of Model Fit value is 167.704 (112), p=0.005, and $RMSEA$ = 0.08, CFI=0.88, TLI=0.83, $SRMR$ = 0.097. Significant paths were: $MAR \rightarrow CAR$ 0.09 (0.04) and $MGR \rightarrow CGR$ 0.09 (0.03). Covariances were: $CAR – CBR$ –0.09 (0.01), $CAR – CGR$ –0.07 (0.01), $CCR – CDR$ –0.12 (0.00), $CER – CDR$ 0.07 (0.04), $CBR – CFR$ –0.13 (0.00), $CDR – CFR$ –0.13 (0.01), $CDR – CHR$ –0.12 (0.00), $CER – CFR$ –0.14 (0.00), $CER – CHR$ –0.06 (0.05) and $CGH – CHR$ –0.06 (0.05).

The result and conclusion from the interdependence model presented above is that the research among family members assumes the interdependence of profiles preferences (due to social interactions and non-independence data).

5. Conclusions

In Polish families, mothers (not fathers – as we expected) play the most important role in shaping children's preferences when dealing with bank accounts. So the child is not so independent when making choices concerning a bank account. The most important attribute is access to the bank account via mobile devices and the commission. The most attractive profile was the 7th profile: bank account with access via mobile devices, with some commission, but with returns for credit card usage. This account does not allow to withdraw money for free from foreign ATM machines and the credit card is not free of charges. The Thurstone model allows to compare objects (object × object). The Rasch model allows to compare subject (respondent) × object. The next research goal is to incorporate multilevel analysis (households).

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