THESISES OF THE DOCTORAL (PhD) DISSERTATION

DISCRETE CHOICE EXPERIMENT – MODELLING OF THE TREATMENT OF PREFERENCE HETEROGENEITY

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1. BACKGROUND, OBJECTIVES AND PRESENTATION OF THE RESEARCH HYPOTHESES

The form of dealing with heterogeneity in preferences is still a recurring key issue in the literature on modelling the discrete choice experiment (DCE). HESS (2014) puts it this way: "The treatment of heterogeneity across individual decision makers is one of the key topics of research in choice modelling…" (HESS, 2014, 311. p.). The assumption of homogeneous preferences inherent in the multinomial logit (MNL) specification associated with the name of MCFADDEN (1974) has been attempted to be successfully addressed by researchers using discrete on the one hand and continuous distributions on the other. The former approach became known as latent class (LC), while the latter became known as random parameter (RPL) modelling (BOXALL and ADAMOWICZ, 2002; GREENE and HENSHER, 2003; SHEN and SAIJO, 2009; SHEN, 2009; ORTEGA et al., 2011; GRACIA and DE-MAGISTRIS, 2013; GOOSSENS et al., 2014; SCHULZ et al., 2014; SCHAAK and MUSSHOFF, 2020). The same limitation is intended to be solved by the random parameter latent class (RLC) specification, which nests the latter two solutions and, in addition to forming a discrete number of classes with distinct preferences, similar to LC, in the tastes of consumers in each class, it also examines inherent differences (similar to RPL, through the use of predetermined, continuous distributions) (BUJOSA et al., 2010; GREENE and HENSHER, 2013).

Nothing proves the importance of the topic I want to examine better than it is possible to estimate models that show a significantly better fit through the treatment of the assumption as mentioned earlier of homogeneous preferences. As a result, a more accurate picture can be obtained of consumer behaviour and its underlying factors.

Objectives of the research

1. To examine whether models that attempt to address differences in tastes show a better fit than MNL specification, which assumes homogeneous preferences.
2. To examine whether complementing the MNL and RPL models with interactions leads to better-fitting models.
3. To examine whether a clear ranking can be established between LC (attempting to handle preference heterogeneity by using discrete distributions) and RPL (trying to

address preference heterogeneity by using continuous distributions) models based on their fit.

4. To examine whether the simultaneous application of discrete and continuous distributions (RLC model) will undoubtedly result in a better fit model than the further specifications analysed.
5. To examine whether there is a significant difference in the case of the MNL model between the direct and indirect approaches of the willingness to pay (WTP) calculation.

Hypotheses of the research

H1: Compared to the MNL model, which assumes homogeneous preferences, all other specifications that attempt to address differences in taste perform better.

The multinomial logit specification associated with the name MCFADDEN (1974) is still widely used today, but due to its limitations, it is already a culmination of the analytical structure in a few cases. The primary reason for this is the assumption of homogeneous preferences. There are already many specifications available to analysts to address this problem, intending to reach a more accurate model estimation. The importance of the topic is proved by the fact that book chapters are also about possible solutions (HESS, 2014; MARIEL et al., 2021).

H2: Complementing the MNL and RPL models with interactions clearly results in better-fitting models.

In addition to the main effects of the attributes examined in the experiment, various interactions (these can be formed, for example, from variables related to sociodemographic characteristics) can be incorporated into our model to be estimated to address heterogeneity in preferences systematically.

WARBURG et al. (2006) incorporated interactions formed from variables related to sociodemographic characteristics into their multinomial logit and random parameter logit models. Based on their results, the fit of the MNL with interactions outperforms the base (non-interactions) model, which was also confirmed for RPL. Improvement in fit was also achieved through the incorporation of interactions into the model by DEMARTINI et al. (2018), WANG et al. (2018), and MUNTINGH et al. (2019). It is important to note, however, that these conclusions are based on log-likelihood and Pseudo R^2 values, which do not correct with the number of estimated parameters. By defining the Bayesian information criterion (BIC), a much more nuanced picture becomes visible. Based on the BIC, the base model shows a better fit for two authors, while the interaction model also shows a better fit for two authors.

H3: To capture the heterogeneity inherent in preferences, a clear ranking can be established between model specifications that use discrete and continuous distributions based on their model fit.

In the practice of discrete choice modelling, two directions have primarily spread to model the treatment of preference heterogeneity. The first of these is the latent class approach, which attempts to solve the problem by creating a discrete number of classes with distinct tastes. The other direction is the random parameter logit modelling, which allows utility coefficients to vary with predetermined distributions among respondents.

GREENE and HENSHER (2003), through the comparison of the LC and RPL models, concluded that both specifications performed excellently for their data sets examined (the LC model showed minimally better fit). Consequently, the authors suggest further comparisons on other samples. SCARPA et al. (2005) were also unable to draw a clear consistency, as in one of the analysed samples, the fit of the LC and the other of the RPL specification already seemed to be better. Research to compare LC and RPL models was also conducted by SHEN (2009), who concluded that the LC specification performed better than both of its data sets examined. However, it is necessary to point out that the author warns against making statements that the LC model would outperform the RPL in all situations.

H4: Simultaneous application of discrete and continuous distributions undoubtedly results in a better fit model than the additional specifications analysed.

In addition to the ability for analysts to manage heterogeneity in preferences through the use of discrete (LC modelling) and continuous (using the RPL specification) distributions, their combined application (development of an RLC model) can be implemented to achieve an even more complex picture. BUJOSA et al. (2010) justify the use of the RLC specification on the grounds that in the case of LC modelling, a significant proportion of unexplained variability may remain within the developed classes, so the use of random parameters may become justified. Their results confirm all this, as their RLC model (based on the obtained fit indicators) exceeds both the LC and RPL specifications. GREENE and HENSHER (2013) also compared these models, concluding that the combination of LC and RPL specifications leads to a clear fit improvement.

H5: There is no significant difference between the direct and indirect approaches of willingness to pay calculations for the MNL model.

To deal with preference heterogeneity, in many cases, random parameters are estimated during modelling. However, this can lead to the derivation of willingness to pay calculations (indirect calculation) becoming problematic. This is because there are no finite moments in the ratio of certain distributions, as DALY et al. (2012) have pointed out. To avoid all this, an extremely advantageous alternative for analysts is to estimate in willingness to pay space (direct calculation). In this case, the distributions are already defined for the WTP parameter itself (TRAIN and WEEKS, 2005). Transforming our utility function (using WTP space) can also be an advantage in that we do not need to use additional methods (such as the delta method) to determine standard errors (BLIEMER and ROSE, 2013). It is necessary to recognise that since the MNL specification estimates fixed parameters, the advantage as mentioned above is not exploited, but for the latter, it may be a favourable alternative for all researchers as it proves a simpler option and leads to the same result as indirect calculation.

2. DATABASE AND DESCRIPTION OF THE METHODS USED

In this chapter, I will describe the details of three experiments on which the research of my dissertation is based. The first examined consumer preferences for margarine, the second for traditional mangalica sausage, and the third for sliced packaged sausage. After presenting the research process, the experimental designs, and the composition of the samples, I move on to the methodological approach I want to use in my analyses. Here I will discuss four types of model specifications, different model fit indicators, and two approaches to calculating willingness to pay.

2.1. Presentation of experiments

In this subchapter, I will present three experiments that formed the empirical part of my dissertation.

2.1.1. Examination of consumer preferences for margarine among university students (Experiment 1)

The research was carried out in the period between October and November 2019 at the Faculty of Economics and Business of the University of Debrecen. We conducted the survey first among Hungarian students and then among international students studying in Hungary. This was preceded by a detailed literature review and focus group interviews on identifying the attributes that most influence consumer preferences and their levels concerning the product under study (margarine). Details are illustrated in *Table 1*.

Table 1: **Attributes, their description, and their levels in the experiment (Experiment 1)**

Attribute	Description	Attribute level
Price	The purchase price of a product in a package of 450-500 grams, expressed in HUF.	350
		450
		550
Fat content	The fat content of the product is expressed per 100 grams, expressed as a percentage.	<31
		31-50
		50<
Salt content	The salt content of the product is expressed per 100 grams, expressed as a percentage.	<0.51
		0.51-0.8
		0.8<
Sunflower oil content	Information on whether the product contains sunflower oil.	Contain
		Does not contain

Source: Based on CZINE and BALOGH, 2020

In the next step, the type of experimental design was chosen. In the so-called "full factorial" case, where all possible product combinations are taken into account, we should have included $2^1 \times 3^3 = 54$ options in our decision situations. This number was considered too large, so we chose the "D-efficient" design from the group of "fractional factorial" designs. This reduces the number of product alternatives while minimising design errors (D-errors) (ROSE and BLIEMER, 2014). This was accomplished through the use of Ngene 1.2 software (CHOICEMETRICS, 2018). In the final questionnaire, we presented eight choice situations, each of which contained three alternatives. We did not include the no-answer/no-purchase option, so we put our fillers in front of a kind of "forced choice". An example of a decision situation is shown in *Table 2*.

Table 2: **Example of a decision situation (Experiment 1)**

	Alternative 1	Alternative 2	Alternative 3
Price (450-500 g)	450 HUF	350 HUF	550 HUF
Fat content	50%<	<31%	<31%
Salt content	<0.51%	0.51-0.8%	0.51-0.8%
Sunflower oil content	Contain	Contain	Does not contain
Your choice (X):			

Source: Based on CZINE and BALOGH, 2020

It is important to mention that the filling was done through a convenience sampling procedure, so the conclusions drawn from the analyses are not suitable for generalisation. Our primary goal was to test the applicability of the methodology in the present context. Details of the composition of our sample are shown in *Table 3*.

Table 3: **Presentation of sample details (Experiment 1)**

Sociodemographic variables	Hungarian sample (N=150)	International sample (N=134)
Gender (%)		
Male	34.7	52.3
Female	65.3	44.0
Did not respond	0.0	3.7
Age (mean)	20.6	22.2
Age (standard deviation)	1.4	3.2
Highest level of education (%)		
Graduation	86.4	23.9
Graduation and further qualification	13.6	74.6
Did not respond	0.0	1.5
Monthly net income (per capita) (%)		
Income category 1	21.2	32.1
Income category 2	35.7	34.3
Income category 3	21.9	16.4
Income category 4	21.2	14.2
Did not respond	0.0	3.0
Residence (%)		
Township	19.0	2.2
Small town	25.2	6.7
Medium city	11.6	28.4
Big city	44.2	61.9
Did not respond	0.0	0.8
Marital status (%)		
Single	80.1	87.3
Life partner/Married	19.9	12.7

Source: Based on CZINE and BALOGH, 2020

Note: Income category 1: < 150 000 HUF (< 500 €), Income category 2: 150 001–250 000 HUF (501–800 €), Income category 3: 250 001–350 000 HUF (801–1 100 €), Income category 4: 350 001 HUF < (1 101 € <).

Further details on the research process can be found in CZINE et al. (2019; 2020c).

2.1.2. Investigation of consumer preferences for mangalica sausage in the Northern Great Plain region (Experiment 2)

Our research on the assessment of consumer preferences for traditional mangalica sausage was carried out between December 2019 and February 2020 in three cities of the Northern Great Plain region (Nyíregyháza, Debrecen, Szolnok). The product attributes, their description and their levels determined based on the literature and focus group interviews are presented in *Table 4*.

Table 4: **Attributes, their description, and their levels in the experiment (Experiment 2)**

Attribute	Description	Attribute level
Price	The purchase price of the product, expressed in HUF, for a quantity of 1 kg.	1500
		2000
		2500
		3000
Meat content	The mangalica meat content of the product, expressed as a percentage.	50
		75
		100
Label of origin	Information on whether the product has a label of origin.	Yes
		No
Place of purchase	Information on where to purchase the product.	Farmers' market
		Butcher
		Hyper-/supermarket

Source: Based on CZINE et al., 2020a

A D-efficient experimental design was used to compile the decision situations. Our choice was justified by the fact that the number of product alternatives that could be compiled for the full factorial design was considered too large $4^1 \times 3^2 \times 2^1 = 72$. This resulted in eight decision situations where three alternatives were included in each case. One of these options has always been "opt-out". An example of a decision situation is shown in *Table 5*.

Table 5: **Example of a decision situation (Experiment 2)**

	Alternative 1	Alternative 2	No choice
Price (1000 g)	3000 HUF	2000 HUF	-
Meat content	75 %	75 %	-
Label of origin	Yes	No	-
Place of purchase	Farmers' market	Butcher	-
Your choice (X):			

Source: Based on CZINE et al., 2020a

Our data were collected through a quota sampling procedure. Our sample contains 477 persons (with the distribution of Nyíregyháza-155, Debrecen-165, Szolnok-157), which can be considered representative of the region by gender, age and residence. Detailed distributions are shown in *Table 6*.

Table 6: **Presentation of sample details (Experiment 2)**

Sociodemographic variables	Sample (N=477)	Regional distribution
Gender (%)		
Male	44.0	48.3
Female	56.0	51.7
Age (category) (%)		
Age group 1	22.0	21.8
Age group 2	26.5	27.1
Age group 3	22.0	21.0
Age group 4	29.5	30.1
Highest level of education (%)		
Elementary	8.2	-
Secondary	44.6	-
Higher education	47.2	-
Monthly gross income (category) (%)		
Substantially below average	33.3	-
Below average	17.6	-
Average	25.8	-
Above average	23.3	-
Residence		
Urban	27.7	31.7
Rural	72.3	68.3

Source: Based on CZINE et al., 2020a; KSH, 2020a and KSH, 2020b

Note: Age group 1: < 30 year, Age group 2: 30–39 year, Age group 3: 40–49 year, Age group 4: 50 year <.

Further details on the research process can be found in CZINE et al. (2020a; 2020b).

2.1.3. Investigation of consumer preferences for sliced packaged sausage among Hungarian consumers (Experiment 3)

The data collection of our research aimed at surveying the preferences for sliced packaged sausages was carried out by the LIGHTSPEED research institute in the summer of 2018 online among the Hungarian population. Similar to the two studies described earlier, this experiment began with reviewing the literature and conducting focus group interviews. The questionnaire was first prepared in English, also using the expertise of international researchers. It was then translated into Hungarian, which meant the final form. The product attributes included in the study, their descriptions, and their levels are shown in *Table 7*.

Table 7: **Attributes, their description, and their levels in the experiment (Experiment 3)**

Attribute	Description	Attribute level
Price	The purchase price of a sliced packaged product weighing 80 grams, expressed in HUF.	189
		279
		369
		459
Label	Information on whether the product is branded and, if so, what it is.	Sausage with no certificate
		Gyulai sausage
		Pick sausage
Taste	Information on whether the product has additional spicy and, if so, to what extend.	No further spicy
		Further spicy
		Further extra spicy

Source: Own editing, 2021

Similar to the research described earlier, a D-efficient experimental design was used to compile the decision situations. Six decision situations were included in the final questionnaire. Each of these had three product alternatives and a "no choice" option. An example of a decision situation is shown in *Figure 1*.

Figure 1: **Example of a decision situation (Experiment 3)**

Source: Own editing, 2021

Details of our sample, which was cleared of incomplete responses (containing 380 fillers), are shown in *Table 8*.

Table 8: **Presentation of sample details (Experiment 3)**

Sociodemographic variables	Sample (N=380)	Hungary
Gender (%)		
Male	50.5	47.8
Female	49.5	52.2
Age (category) (%)		
Age group 1	23.1	32.8
Age group 2	21.6	11.7
Age group 3	24.2	16.3
Age group 4	31.1	39.2
Highest level of education (%)		
Education level 1	31.3	51.8
Education level 2	25.5	29.5
Education level 3	43.2	18.7
Monthly net income (category) (%)		244 609 HUF/month
Income category 1	6.3	
Income category 2	11.6	
Income category 3	11.6	
Income category 4	38.7	
Income category 5	30.0	
Income category 6	1.8	
Residence		
Rural	16.8	29.5
Urban (non-cities)	36.3	32.6
City	46.9	37.9
Household size (mean)	2.9	2.9
Number of children (<18 year) in a household (mean)	0.6	1.1

Source: Own editing, 2021; Based on KSH, 2020a and KSH, 2020b

Note: Age group 1: < 30 year, Age group 2: 30–39 year, Age group 3: 40–49 year, Age group 4: 50 year <; Education level 1: Upper secondary/lower secondary/primary education or below; Education level 2: University or college entrance qualification; Education level 3: Bachelor's, Master's or doctoral degree; Income category 1: < 150 000 HUF; Income category 2: 150 001–205 000 HUF; Income category 3: 205 001–235 000 HUF; Income category 4: 235 001–380 000 HUF; Income category 5: 380 001–835 000 HUF; Income category 6: 835 000 HUF <.

From *Table 8*, it can be seen that although we are already talking about a cleared sample, the representativeness can only be considered clearly satisfactory for those living in one household. It is somewhat biased towards male consumers and households with fewer children, while over-represented among middle-aged, more educated, urban respondents, due to a kind of limitation of online questionnaire surveys (BETHLEHEM, 2010).

2.2. Model specifications, fit indicators and determination of willingness to pay

I will process the data (related to discrete choice modelling) from the three studies described earlier with the R Apollo package, using four specifications, which are as follows: (1) multinomial logit (MNL) model, (2) random parameter logit (RPL) model, (3) latent class (LC) model, (4) random parameter latent class (RLC) model (HESS and PALMA, 2019a; HESS and PALMA, 2019b; R CORE TEAM, 2020). I will discuss their characteristics, three model fit indicators (Pseudo R^2, Akaike information criterion (AIC), Bayesian information criterion (BIC)) and two approaches to calculating willingness to pay (WTP) below.

2.2.1. Multinomial logit (MNL) model

The multinomial logit model associated with the name MCFADDEN (1974) is considered one of the oldest specifications used since. Its advantageous properties include that it is relatively easy to estimate, and the interpretation of its results does not involve many problems. Today, however, it is increasingly rare for researchers to rely solely on conclusions drawn from this model. Therefore, on the one hand, it can be blamed for making homogeneous preferences for respondents likely. This would suggest that all examined persons have the same level of sensitivity for the attributes analysed. On the other hand, it presupposes the independence of irrelevant alternatives (there is no correlation between the alternatives of the choice situation). As a result of these factors, the specification is primarily used to establish (gain prior knowledge of the effects of the attributes under study) further more complex specifications (FIEBIG et al., 2010). In the case of the model, the systematic part of the utility can be written according to *Equation 1*.

$$V_{n,i} = \sum_{k=1}^{K} \beta_k X_{n,i,k}, \tag{1}$$

where *n* is the respondent, *i* is the alternative, *k* is the examined product attribute, β is the coefficient estimated for the *k*-th attribute, *X* is the observed variable, and $V_{n,i}$ is the systematic part of the utility of the *n*-th respondent for the *i*-th alternative (MCFADDEN, 1974).

In the case of the model, the probability of the *n*-th decision makers' choice for the *i*-th alternative from option *J* can be written according to *Equation 2* (MCFADDEN, 1974).

$$P_{n,i} = \frac{exp\ \sum_{k=1}^{K} \beta_k X_{n,i,k}}{\sum_{j=1}^{J} exp \sum_{k=1}^{K} \beta_k X_{n,j,k}} \tag{2}$$

2.2.2. Random parameter logit (RPL) model

The so-called random parameter logit model can capture the heterogeneity inherent in individuals' preferences. It makes all this possible by allowing the coefficients for each attribute to vary along with a predetermined distribution among respondents and estimating certain of their parameters (e.g. expected value, standard deviation). The distributions used for the attributes (e.g. normal, log-normal, uniform, log-uniform) are based on the researcher's decision. It is important to mention that the model estimation requires the use of a simulation procedure, which is most often performed with so-called "Halton-draws" (FOSGERAU and BIERLAIRE, 2007). Finally, it should be emphasised that RPL can also address another disadvantage of the MNL model, the assumption of independence of irrelevant alternatives. It accomplishes this by allowing a flexible variance-covariance structure for the error term (for the unobservable part of the utility) (TRAIN and WEEKS, 2005). In the case of the model, the systematic part of the utility can be written according to *Equation 3*.

$$V_{n,i} = \sum_{k=1}^{K} \beta_{n,k}\, X_{n,i,k}, \tag{3}$$

where $\beta_{n,k}$ can be decomposed according to *Equation 4*.

$$\beta_{n,k} = \bar{\beta}_k + \sigma_{n,k}, \tag{4}$$

where $\bar{\beta}_k$ is the mean member, and $\sigma_{n,k}$ indicates a respondent-dependent deviation (TRAIN, 2009).

In the case of the model, the probability of the *n*-th decision makers' choice for the *i*-th alternative is modified according to *Equation 5* compared to that presented in the MNL model (*Equation 2*).

$$P_{n,i}\ (\Omega) = \int_{\beta} P_{n,i}\ (\beta) f(\beta|\Omega)\ d\beta, \tag{5}$$

where $P_{n,i}$ is the choice probability presented for the MNL model, Ω denotes the parameters of the coefficient β (assuming it follows a random distribution), while $f(\beta|\Omega)$ denotes the density function for the coefficient β (HESS, 2014).

2.2.3. Latent class (LC) model

Another direction of capturing differences in taste is represented by so-called latent class modelling. This specification seeks to approximate heterogeneity in preferences through the formulation of a discrete number of classes. The classes of the model, often referred to in the literature as "semi parametric" solutions, are heterogeneous (each class has different β parameters), but their member can be characterised by homogeneous preferences. For the model, the systematic part of the utility can be written according to *Equation 6*.

$$V_{n,i|q} = \sum_{k=1}^{K} \beta_{q,k} X_{n,i,k}, \tag{6}$$

where $\beta_{q,k}$ for the *q*-th class (*q* = 1,…,*Q*), denotes the parameter for the *k*-th attribute (BOXALL and ADAMOWICZ, 2002).

In the case of the model, the probability of choosing the *i*-th alternative from option *J* for the *n*-th decision-maker, which can be classified into the *q*-th class, can be written according to *Equation 7*.

$$P_{n,i|q} = \frac{\exp \sum_{k=1}^{K}(\beta_{q,k} X_{n,i,k})}{\sum_{j=1}^{J} \exp \sum_{k=1}^{K}(\beta_{q,k} X_{n,j,k})}, \text{ q} = 1,\dots,\text{Q} \tag{7}$$

It is clear from *Equation 7* that it is structured according to a similar composition to that shown for MNL. However, to determine the probability of individuals falling into different classes and thereby trying to explain the heterogeneity inherent in taste, *Equation 7* is supplemented according to *Equation 8*.

$$P_{n,i} = \sum_{q=1}^{Q} P_{n,i|q} H_{n,q}, \tag{8}$$

where $H_{n,q}$ denotes the probability that the *n*-th person will be fall in the *q*-th class (GREENE and HENSHER, 2003).

Choosing the ideal number of classes is an important issue in the practice of LC modelling. This is usually decided based on information criteria (e.g. Pseudo R^2, AIC, BIC), which I will provide a more detailed overview later (LOUVIERE et al., 2000; CAVANAUGH and NEATH, 2019).

2.2.4. Random parameter latent class (RLC) model

An extension of LC, the so-called random parameter latent class model, combines the properties of the RPL and LC models. It does all this by allowing the heterogeneity of preferences to be captured not only between classes but also within them (BUJOSA et al., 2010). For the model, within-class heterogeneity develops according to *Equation 9* (GREENE and HENSHER, 2013).

$$\beta_{n|q,k} = \beta_{q,k} + \sigma_{n|q,k}, \tag{9}$$

where $\sigma_{n|q,k}$ can be written according to *Equation 10*.

$$\sigma_{n|q,k} \sim E[\sigma_{n|q,k} \mid X] = 0,\ Var[\sigma_{n|q,k} \mid X] = \sum q, \tag{10}$$

where q indicates the given group, and σ_n the respondent-dependent deviation, while X indicates that $\sigma_{n|q,k}$ does not correlate with any of the data in the sample (GREENE and HENSHER, 2013).

In the case of the model, the probability of the conditional choice of the *n*-th person among alternatives *I* can be written according to *Equation 11*.

$$f[y_{n,t} \mid (\beta_q + \sigma_n), X_{n,t}] = \frac{\exp\,[\sum_{i=1}^{I} y_{n,t,i}(\beta_q+\sigma_n)X_{n,t,i}]}{\sum_{i=1}^{I} \exp\,[\sum_{i=1}^{I} y_{n,t,i}(\beta_q+\sigma_n)X_{n,t,i}]}\ i = 1,\ldots,I, \tag{11}$$

where *t* is the decision situation; $X_{n,t,i}$ denotes the observed variable for the *i*-th alternative for the *n*-th decision-maker in the *t*-th decision situation; while $y_{n,t,i}$ = 1, if the *i*-th alternative was chosen from option *I*, in all other cases 0 (GREENE and HENSHER, 2013).

2.2.5. Indicators quantifying the fit of models

Several indicators can be used for the aggregate comparability of the models, of which Pseudo R^2 (*Equation 12.*), AIC (*Equation 13.*) and BIC (*Equation 14.*) are very often used. Analysts can use these to decide, for example, what class number LC specification needs to be estimated to achieve the best model fit (MARIEL et al., 2021).

$$Pseudo\ R^2 = 1 - \frac{LL}{LL_0}, \tag{12}$$

where *LL* is the log-likelihood value for the final model, and LL_0 is the log-likelihood value for the model with only constant members.

$$AIC = -2LL + 2k, \tag{13}$$

where k is the number of estimated parameters.

$$BIC = -2LL + k\ln(n), \tag{14}$$

where n is the number of observations.

It is necessary to mention that the Pseudo R^2 indicator is not the same as the R^2 value known from linear regression analysis. The difference between them is shown in *Figure 2*.

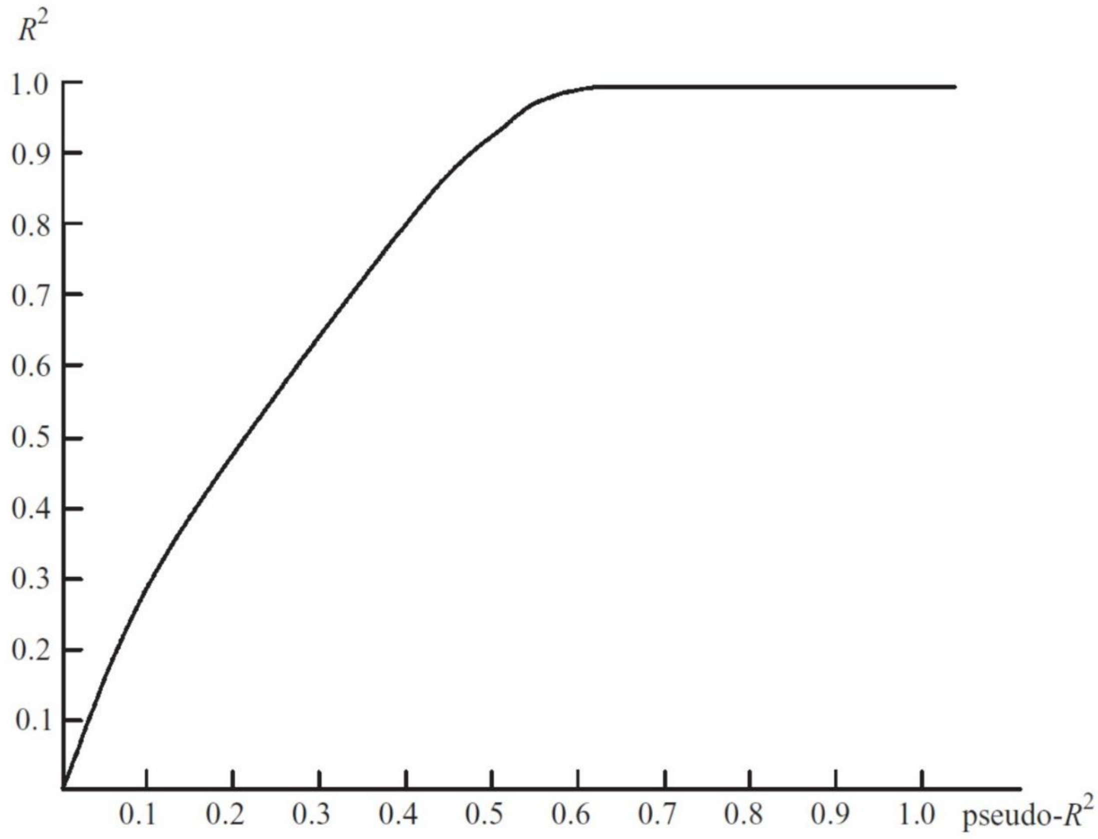

Figure 2: **Comparison of R^2 and Pseudo R^2 indicators**

Source: Based on HENSHER et al., 2015

It can be clearly seen from *Figure 2* that, for example, a Pseudo R^2 value of 0,3 corresponds to an R^2 value of about 0,6.

2.2.6. Willingness to pay (WTP) calculations

If price is also included in the examined product/service attributes, the determination of willingness to pay is also an important point in the practice of discrete choice experiments. With the calculation, we can answer questions about how much a change in a particular product/service attribute is associated with the willingness to pay. The calculation of WTP for specific attributes can be done according to *Equation 15*, while the delta method can derive their standard errors (HOLE, 2007; HENSHER et al., 2015).

$$WTP_{Attribute} = (-1)\frac{\beta_{Attribute}}{\beta_{Price}}, \tag{15}$$

where $WTP_{Attribute}$ is the willingness to pay for the examined attribute; $\beta_{Attribute}$ indicates the estimated value of the utility coefficient for the examined attribute, while β_{Price} indicates the value of the utility coefficient for the price.

It is necessary to mention that we can also make a direct estimate of the willingness to pay, the so-called "WTP space", which can be achieved by transforming our utility function. An example of this is shown in *Equation 16* (traditional utility function in the preference space) and *Equation 17* (transformed utility function in the WTP space) (TRAIN and WEEKS, 2005).

$$V_{n,i,t} = \beta_{Price}Price_{n,i,t} + \beta_{Attribute\ 1}Attribute\ 1_{n,i,t} + \beta_{Attribute\ 2}Attribute\ 2_{n,i,t} + \beta_{Attribute\ 3}Attribute\ 3_{n,i,t}, \tag{16}$$

where β_{Price}, $\beta_{Attribute\ 1}$, $\beta_{Attribute\ 2}$, $\beta_{Attribute\ 3}$ are the estimated coefficient for the price and the 1., 2. and 3. attributes.

$$V_{n,i,t} = \beta_{Price}(Price_{n,i,t} + WTP_{Attribute\ 1}Attribute\ 1_{n,i,t} + WTP_{Attribute\ 2}Attribute\ 2_{n,i,t} + WTP_{Attribute\ 3}Attribute\ 3_{n,i,t}), \tag{17}$$

where $WTP_{Attribute\ 1}$, $WTP_{Attribute\ 2}$ and $WTP_{Attribute\ 3}$ are the estimated WTP for the 1., 2. and 3. attributes.

3. MAIN FINDINGS OF THE DISSERTATION

In my research, I examined different modelling aspects of the discrete choice experiment. Based on my results, I can decide on my hypotheses as follows:

H1: Compared to the MNL model, which assumes homogeneous preferences, all other specifications that attempt to address differences in taste perform better.

I give a clear answer to my first hypotheses with the results summarised in *Table 9*.

Table 9: **Values of information criteria for each model**

Experiment 1					
Information criteria	**MNL**	**RPL**	**LC (3 classes)**	**LC (2 classes)**	**RLC (2 classes)**
Pseudo R^2	0.06	0.14	0.14	0.11	0.16
Log-likelihood (final)	-2148.95	-1972.15	-1982.82	-2043.34	-1937.90
AIC	4313.89	3970.30	4009.64	4116.68	3925.80
BIC	4359.04	4043.67	4133.81	4201.34	4066.90
Experiment 2					
Information criteria	**MNL**	**RPL**	**LC (3 classes)**	**LC (2 classes)**	**RLC (2 classes)**
Pseudo R^2	0.16	0.24	0.29	0.26	0.28
Log-likelihood (final)	-3518.23	-3176.09	-2993.28	-3109.58	-3026.35
AIC	7052.45	6374.17	6058.56	6249.15	6094.70
BIC	7102.43	6442.89	6283.45	6342.86	6225.89
Experiment 3					
Information criteria	**MNL**	**RPL**	**LC (4 classes)**	**LC (2 classes)**	**RLC (2 classes)**
Pseudo R^2	0.15	0.28	0.28	0.24	0.32
Log-likelihood (final)	-2693.72	-2264.53	-2271.03	-2399.05	-2161.86
AIC	5403.44	4555.05	4600.06	4828.09	4373.71
BIC	5449.30	4629.57	4766.29	4914.07	4517.01

Source: Own editing, 2021

Based on the values in *Table 9.*, it can be seen that for all three experiments, both the RPL and LC (LC and RLC) models clearly fit better than the MNL specification (the Pseudo R^2 indicator is higher in all cases, while the log-likelihood (final), AIC and BIC are smaller).

Based on these, **I confirm my hypothesis 1.**

H2: Complementing the MNL and RPL models with interactions clearly results in better-fitting models.

Regarding my second hypothesis, the values presented in *Table 10* formed the basis of my decision.

Table 10: **Values of information criteria for base and interaction models***

Experiment 2				
Information criteria	**MNL**	**MNL (interaction)**	**RPL**	**RPL (interaction)**
Pseudo R^2	0.16	0.18	0.24	0.25
Log-likelihood (final)	-3518.23	-3438.07	-3176.09	-3139.09
AIC	7052.45	6920.13	6374.17	6328.18
BIC	7102.43	7057.57	6442.89	6484.35
Experiment 3				
Information criteria	**MNL**	**MNL (interaction)**	**RPL**	**RPL (interaction)**
Pseudo R^2	0.15	0.16	0.28	0.29
Log-likelihood (final)	-2693.72	-2667.53	-2264.53	-2247.02
AIC	5403.44	5379.05	4555.05	4548.03
BIC	5449.30	5505.16	4629.57	4702.79

Source: Own editing, 2021

Note: *In the case of the first experiment, the interactions did not represent a significant effect, so it was not relevant in testing the present hypothesis.

Based on the results in *Table 10*, only for the second experiment, the MNL specification shows a clear (supported by all information criteria) improvement in model fit compared to the base (non-interaction) model. For the RPL specifications of the second experiment and the MNL and RPL specifications of the third experiment, the value of the Bayesian information criterion increased, suggesting a weaker fit.

Based on these, **I reject my hypothesis 2.**

H3: To capture the heterogeneity inherent in preferences, a clear ranking can be established between model specifications that use discrete and continuous distributions based on their model fit.

Regarding my third hypothesis, I made a decision based on the values of the information criteria presented in *Table 11*.

Table 11: **Values of information criteria for RPL and LC specifications**

Experiment 1		
Information criteria	**RPL**	**LC* (3 classes)**
Pseudo R^2	0.14	0.14
Log-likelihood (final)	-1972.15	-1982.82
AIC	3970.30	4009.64
BIC	4043.67	4133.81
Experiment 2		
Information criteria	**RPL**	**LC* (3 classes)**
Pseudo R^2	0.24	0.29
Log-likelihood (final)	-3176.09	-2993.28
AIC	6374.17	6058.56
BIC	6442.89	6283.45
Experiment 3		
Information criteria	**RPL**	**LC* (4 classes)**
Pseudo R^2	0.28	0.28
Log-likelihood (final)	-2264.53	-2271.03
AIC	4555.05	4600.06
BIC	4629.57	4766.29

Source: Own editing, 2021

Note: *For LC models, I took the class number specifications with the best fit as the basis for comparison.

Based on the results in *Table 11*, no clear trend can be established between specifications attempting to address differences in preferences through the use of discrete (LC model) and continuous (RPL model) distributions. For the first and third experiments (based on all information criteria), the RPL, while for the second, the LC model shows a better fit.

Based on these, **I reject my hypothesis 3.**

H4: Simultaneous application of discrete and continuous distributions undoubtedly results in a better fit model than the additional specifications analysed.

For my fourth hypothesis, I decided based on the values of the information criteria presented in *Table 12*.

Table 12: **Values of information criteria for RPL, LC and RLC specifications**

Experiment 1			
Information criteria	**RPL**	**LC (2 classes)**	**RLC (2 classes)**
Pseudo R^2	0.14	0.11	0.16
Log-likelihood (final)	-1972.15	-2043.34	-1937.90
AIC	3970.30	4116.68	3925.80
BIC	4043.67	4201.34	4066.90
Experiment 2			
Information criteria	**RPL**	**LC (2 classes)**	**RLC (2 classes)**
Pseudo R^2	0.24	0.26	0.28
Log-likelihood (final)	-3176.09	-3109.58	-3026.35
AIC	6374.17	6249.15	6094.70
BIC	6442.89	6342.86	6225.89
Experiment 3			
Information criteria	**RPL**	**LC (2 classes)**	**RLC (2 classes)**
Pseudo R^2	0.28	0.24	0.32
Log-likelihood (final)	-2264.53	-2399.05	-2161.86
AIC	4555.05	4828.09	4373.71
BIC	4629.57	4914.07	4517.01

Source: Own editing, 2021

From the results in *Table 12*, it is clear that the RLC model shows the best fit for all three experiments, based on all information criteria. The only exception to this is the BIC value seen in the first experiment (whose data represented a lower level of quality).

Based on these, **I confirm my hypothesis 4.**

H5: There is no significant difference between the direct and indirect approaches of willingness to pay calculations for the MNL model.

Regarding my fifth hypothesis, I decided based on the values of the WTP calculations presented in *Table 13*.

Table 13: **Results of WTP calculation modes for the MNL model**

Experiment 1		
Product attributes	WTP (Delta method)	WTP (WTP space estimation)
Medium fat content	-124.17***	-124.36***
High fat content	-351.17***	-365.58***
Medium salt content	-126.43***	-128.60***
High salt content	-219.36***	-224.71***
Contains sunflower oil	-23.62	-27.64
Experiment 2		
Product attributes	WTP (Delta method)	WTP (WTP space estimation)
75% mangalica meat content	787.20***	787.30***
100% mangalica meat content	953.50***	953.50***
Label of origin	2 081.70***	2 081.60***
Butcher	-857.60***	-857.60***
Hyper-/supermarket	-1 139.30***	-1 139.30***
Experiment 3		
Product attributes	WTP (Delta method)	WTP (WTP space estimation)
Gyulai label	134.51***	134.51***
Pick label	124.04***	124.04***
Further spicy	-60.78***	-60.78***
Further extra spicy	-160.24***	-160.24***

Source: Own editing, 2021

Note: *** Significant at the 1% level.

Based on the results in *Table 13*, there are minor differences between the direct and indirect calculation methods only for the first experiment. The other two preference studies show almost perfect agreement between the approaches.

Based on these, **I confirm my hypothesis 5.**

4. NEW AND NOVEL RESULTS OF THE DISSERTATION

Based on my research, I can make the following new and novel statement at the **international level**:

1) I have shown that ***the simultaneous application of discrete and continuous distributions (RLC model estimation) to deal with taste differences clearly outperforms the other specifications (LC and RPL model types) I have examined.*** In a new area application context, this result confirms the conclusions of BUJOSA et al. (2010) and GREENE and HENSHER (2013).

Based on my research, I can make the following new and novel findings at the **Hungarian level**:

2) Based on my literature review of the four application areas of the discrete choice experiment, ***I pointed out that there are correlations between the area and the addressing key issues of the procedure*** (e.g. format of the alternatives, type of the estimated model specifications). My study followed similar perspectives as the research of SOEKHAI et al. (2019); however, in contrast to them, not within a given area of application but also among the four most common areas of application appearing in BAJI (2012) study.
3) ***Through the analysis of various information criteria that quantify the fit of the models, I have shown that any specification that attempts to address heterogeneity in preferences (LC, RPL, RLC model types) shows a better fit compared to the MNL model.*** Based on this result, it is not enough to stop and draw overall conclusions from an MNL model estimate. A similar result can be seen in the Hungarian literature in the study of BRANDTMÜLLER (2009) and several international book chapters (e.g. TRAIN (2009), HESS (2014), HENSHER et al. (2015), MARIEL et al. (2021)) also highlight the importance of the topic.
4) I show that ***extending the MNL and RPL specifications with interactions does not clearly lead (supported by all information criteria) to a better-fitting model*** that is consistent with the conclusions in the international literature (e.g. WARBURG et al. (2006), DEMARTINI et al. (2018), WANG et al. (2018), MUNTINGH et al. (2019)).

5) With my results, I supported that ***a clear sequence cannot be established between specifications that attempt to address heterogeneity in preferences through the use of discrete and continuous distributions (LC and RPL models).*** All this confirms the conclusions of SCARPA et al. (2005) and the suggestions of GREENE and HENSHER (2003) and SHEN (2009) that further comparisons are needed between LC and RPL specifications.

6) I highlighted the fact that ***in the case of the MNL model specification, there is no significant difference in the WTP values regardless of whether it is calculated in direct (willingness to pay estimation) or indirect (derived WTP) form.*** This conclusion confirms the importance of estimating in the WTP space proposed by TRAIN and WEEKS (2005) not only for the application of RPL but also for MNL specification.

5. THE PRACTICAL APPLICABILITY OF THE RESULTS

I believe that my doctoral dissertation can serve as a basis not only for marketing but also for the methodological development of domestic research in several fields. In addition to presenting innovations (primarily modelling) in Hungary at several points in my dissertation, I present the whole process of an internationally prevalent preference assessment procedure in detail that is not visible in previously published works. The empirical review for the idea, the presentation of the process of experiments for the implementation, and the results section can help interpret the estimates and choose the best model.

In addition, the decision-makers of the field of application covered by my dissertation can answer such questions and take measures by similarly examining consumer preferences as introducing a new product/service, pricing and analysing its feature structure for improvements. In addition to the multinomial logit specification, the use of model types that address differences in consumer tastes through the use of discrete (latent class), continuous (random parameter), and possibly mixed (random parameter latent class) distributions can greatly contribute to gain a more accurate and complex picture for these (which may be reflected in model estimates and willingness to pay calculations).

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6. LIST OF PUBLICATIONS RELATED TO THE DISSERTATION

Scientific journal in a foreign language

1. **CZINE, P.** – SZAKÁLY, Z. – BALOGH, P. (2020): A Review of Purchasing Preferences for Margarine among Hungarian and International Students. Studies in Agricultural Economics. 122 : 1 pp. 29-36.
2. **CZINE, P.** – TÖRÖK, Á. – PETŐ, K. – HORVÁTH, P. – BALOGH, P. (2020): The Impact of the Food Labeling and Other Factors on Consumer Preferences Using Discrete Choice Modeling - The Example of Traditional Pork Sausage. Nutrients. 12 : 6.

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3. **CZINE, P.** (2020): A diszkrét választási kísérlet elméleti áttekintése. International Journal of Engineering and Management Sciences. 5 : 1 pp. 62-73.
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List of publications related to the dissertation

Articles, studies (8)

1. **Czine, P.**, Dajnoki, K., Balogh, P.: Diszkrét választási modellek becslése az R Apollo csomagjának használatával - látens osztályú modell.
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12. **Czine, P.**: A kiválasztási tesztek előrejelző képességének vizsgálata a motivációs potenciál vonatkozásában.
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Total IF of journals (all publications): 8,968
Total IF of journals (publications related to the dissertation): 5,717

The Candidate's publication data submitted to the iDEa Tudóstér have been validated by DEENK on the basis of the Journal Citation Report (Impact Factor) database.

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