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WORKPLACE FLEXIBILITY IN POLAND – THE POLYTOMOUS IRT MODELS FORMULATED BY LATENT CLASS APPROACH

Summary: Item response theory is considered to be one of the two trends in methodological assessment of the reliability scale. In turn, latent class models can be viewed as a special case of model-based clustering, for heterogeneous multivariate discrete data. The combination of the two mentioned latent variable models concerns the assumption that the population under study is composed by homogeneous classes of individuals with very similar latent trait levels.

In this approach, the model selection is based on the ordered steps consisting of selecting specific features, such as the number of latent dimensions, the number of latent classes, and the constraints on the item parameters.

The main goal of the paper is to find groups of Poles not currently working for pay with similar workplace flexibility levels and to analyse the (selected) item characteristics of the International Social Survey Programme questionnaire, as well using the discretized variant of polytomous IRT models, formulated by a latent class approach.

Keywords: item response theory, latent class models, polytomous responses.

JEL Classification: C52, J80.

Introduction

The most popular theory of reliability is the classical test theory (CTT). Then, the most common measure of reliability is Cronbach's alpha coefficient. It is worth emphasizing that the methods built on classical test theory require multiple assumptions, e.g. the unidimensionality assumption, which means that all items contribute to measure the same latent trait (i.e. ability in certain subjects, satisfaction level, money saving skills).

Alternative item response theory (IRT) is a model-based theory, established on the idea that the responses to each test item depend on some person and item characteristics, according to specific probabilistic relations. The relationship between unobservable respondent's ability level (the latent trait) and a given item (individual question) can be described by the monotonic non-decreasing function, which is called the item characteristic curve. In the Rasch model [Rasch, 1960] or Birnbaum model [Birnbaum, 1968], this is a parametric logistic function. In the Rasch model (the most prominent example for IRT models), there is only one parameter describing the position of respondents on an unknown continuum of the latent trait. Depending on the IRT model type, the difficulty, discrimination and the guessing item parameters are estimated[1].

In recent years, many IRT models based on the Rasch approach have been built. These include, among others, partial credit model [Masters, 1982], graded response model [Semejima, 1969], rating scale model [Andrich, 1978]. Usually, in most of traditional IRT models such as the Rasch [Rasch, 1960] or two-parameter logistic (2PL) model [Birnbaum, 1968] it is assumed that all items measure the latent trait in the same way for all subjects and all items contribute to measure the same latent trait (unidimensionality assumption). Moreover, a parametric (usually normal) distribution for the latent variable used to represent the trait of interest is explicitly introduced. Unfortunately, in several practical situations these assumptions are too restrictive. Therefore, certain extensions of traditional IRT models have been proposed (for more details, see i.e.: Bacci, Bartolucci, Gnaldi, 2014; Bartolucci, Bacci, Gnaldi, 2014).

Bartolucci [2007] proposed a class of multidimensional latent class item response theory (LC-IRT) models were:

- more latent traits are simultaneously considered and each item is associated with only one of them (*between-item multidimensionality*) [Adams, Wilson, Wang, 1997; Zhang, 2004],
- the latent traits are represented by a random vector with a discrete distribution common to all subjects (each support point of such a distribution identifies a different latent class of individuals).

[1] The guessing parameter expresses the probability that the respondents with very low ability responds positively to an item by chance. The discrimination parameter quantifies how well the item distinguishes between subjects with low/high standing in the continuous latent scale, and the difficulty parameter expresses the difficulty level of the item.

1. IRT models formulated by latent class approach

It is assumed to observe responses of *n* individuals to *j* ($j = 1,\ldots,m$) items of the questionnaire, X_j denotes the response variable for the *j*-th item and $\mathbf{X} = X_1,\ldots,X_m$. This variable has l_j categories denoted by $x = 0,\ldots,l_j - 1$.

Let q be the number of different latent traits measured by the items, $\mathbf{\Theta} = (\Theta_1,\ldots,\Theta_q)'$ is a vector of latent traits and $\boldsymbol{\theta} = (\theta_1,\ldots,\theta_q)'$ one of its possible realizations. The random vector $\mathbf{\Theta}$ is assumed to have a discrete distribution with *u* support points, denoted by $\boldsymbol{\xi}_1,\ldots,\boldsymbol{\xi}_u$ and probabilities $\pi_1,\ldots,\pi_u$, then $\pi_s = p(\mathbf{\Theta} = \boldsymbol{\xi}_s)$.

Let δ_{jd} be a dummy variable equal to 1, if item *j* is assigned to latent trait of type *d* and 0 otherwise ($j = 1,\ldots,m$, $d = 1,\ldots,q$). The conditional response probability that a subject with latent traits (or abilities) levels given by $\boldsymbol{\theta}$ responds by category x to item X_j is given by:

$$p_{jx}(\boldsymbol{\theta}) = p(X_j = x \mid \mathbf{\Theta} = \boldsymbol{\theta}),\ x = 0,\ldots,l_j - 1, \qquad (1)$$

let also $\mathbf{p}_j(\theta)$ denote the probability vector $(p_{j0}(\theta),\ldots,p_{jl_{j-1}}(\theta))'$ that elements of which sum up to 1.

The general formulation of the multidimensional IRT[2] models may be expressed as:

$$g_x(\mathbf{p}_j(\boldsymbol{\theta})) = \alpha_j(\sum_{d=1}^{q}\delta_{jd}\theta_d - \vartheta_{jx}),\ j = 1,\ldots,m,\ s = 1,\ldots,u, \qquad (2)$$

where g_x is a link function specific of category x , α_j and ϑ_{jx} are item parameters identified as discrimination indices and difficulty levels.

On the basis on the specification of the link function and on the basis on the adopted constraints on the item parameters Bartolucci [2007] (see also: Bacci, Bartolucci, Gnaldi, 2014; Bartolucci, Bacci, Gnaldi, 2014) extended the traditional group of undimensional IRT models and i.e. the multidimensional latent class graded response model (LC-GRM, see Eq. 3) is an extension of the GRM by Semejima [1969]. In turn, multidimensional LC rating scale model, given by (4) is an extension of the RSM [Andrich, 1978]:

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[2] This class of Item Response Theory models allow items to measure more than one latent trait (i.e. mathematical and humanistic skills).

$$g_{LC\_GRM}(\mathbf{p}_j(\boldsymbol{\theta})) = \log \frac{p(X_j \geq x \mid \boldsymbol{\Theta} = \boldsymbol{\theta})}{p(X_j < x-1 \mid \boldsymbol{\Theta} = \boldsymbol{\theta})} = \alpha_j (\sum_{d=1}^{q} \delta_{jd} \theta_d - \vartheta_{jx}),$$
$$x = 0, \ldots, l_j - 1, \tag{3}$$

$$g_{LC\_RSM}(\mathbf{p}_j(\boldsymbol{\theta})) = \log \frac{p(X_j = x \mid \boldsymbol{\Theta} = \boldsymbol{\theta})}{p(X_j = x-1 \mid \boldsymbol{\Theta} = \boldsymbol{\theta})} = \sum_{d=1}^{q} \delta_{jd} \theta_d - (\vartheta_{jx} + \tau_x),$$
$$x = 0, \ldots, l_j - 1 \tag{4}$$

where τ_x is the difficulty of the response category x to all items. For binary response variables, Eq. 3 corresponds to multidimensional LC 2PL model and Eq. 4 to the multidimensional LC Rasch model.

All the possible combinations of the item parameters constraints for local and global as well as continuation logit link functions are given in Table 1.

Table 1. Unidimensional IRT models for Ordinal Polytomous Responses

			Link function		
α_j	ϑ_{jx}	**Parameters of the model**	**Global**	**Local**	**Continuation**
free	free	$\alpha_j(\theta - \vartheta_{jx})$	GRM	GPCM	2P-SM
free	constrained	$\alpha_j[\theta - (\vartheta_j + \tau_x)]$	RS-GRM	RS-GPCM	2P-RS-SM
constrained	free	$\theta - \vartheta_{jx}$	1P-GRM	PCM	SRM
constrained	constrained	$\theta - (\vartheta_j + \tau_x)$	1P-RS-GRM	RSM	SRSM

Source: Bartolucci, Bacci, Gnaldi [2016b, p. 127].

RS-GRM abbreviation indicates the rating scale version of the GRM introduced by Muraki [1990], RS-GPCM and 2P-RS-SM are the rating scale versions of GPCM and 2P-SM[3] respectively [Muraki, 1997]; 1P-GRM and 1P-RS-GRM [van der Ark, 2001] are the equally discriminating versions of GRM and RS-GRM, respectively. Finally, SRM and SRSM denote Sequential Rasch Model and the Sequential Rating Scale Model of Tutz [1990].

In the IRT models formulated by latent class approach the discreteness of the random vector $\boldsymbol{\Theta}$ implies that the manifest distribution $\mathbf{X} = (X_1 \ldots, X_m)'$ for all subjects in the *s-th* latent class is equal:

$$p(\mathbf{X} = \mathbf{x}) = \sum_{s=1}^{u} p(\mathbf{X} = \mathbf{x} \mid \boldsymbol{\Theta} = \boldsymbol{\xi}_s)\pi_s. \tag{5}$$

[3] Two-Parameter Sequential Model [Hemker, van der Ark, 2001; van der Ark, 2001] obtained as a special case of the acceleration model of Semejima [1995].

Due to the classical assumption of local independence it can be written as:

$$\begin{aligned} p(\mathbf{x} \mid s) = p(\mathbf{X} = \mathbf{x} \mid \boldsymbol{\Theta} = \boldsymbol{\xi}_s) &= \prod_{j=1}^{m} p(\mathrm{X}_j = x_j \mid \boldsymbol{\Theta} = \boldsymbol{\xi}_s) \\ &= \prod_{d=1}^{q} \prod_{j \in \mathrm{I}_d} p(\mathrm{X}_j = x_j \mid \Theta_d = \xi_{sd}), \end{aligned} \tag{6}$$

where I_d denotes the subset of $\mathrm{I} = 1, \ldots, m$ containing the indices of the items measuring the *d*-th latent trait ($d = 1, \ldots, q$).

2. The model selection procedure

The specification of a multidimensional LC IRT model implies a number of choices. A model selection procedure is based on the following sequence of ordered steps [Bacci, Bartolucci, Gnaldi, 2014]:

- the number of latent classes $s = 1, \ldots, u$,
- link function g_x,
- the constraints on the item parameters (α_j, ϑ_{jx}),
- the number of latent dimensions $d = 1, \ldots, q$.

Parameters estimation for multidimensional IRT models based on discreteness of latent trait is performed using EM algorithm [Dempster, Laird, Rubin, 1977], the selection of the number of latent classes and the type of logit link function on basis of the BIC and AIC indices [Akaike, 1974; Schwarz, 1978], whereas the dimension of the latent trait and the selection of the item discriminating and difficulty parameterization may be performed on the basis of the likelihood ratio (LR) test as well.

LR statistic may be used to test the unidimensionality of a set of items against a specific multidimensional alternative. The null hypothesis is that items in I_{d_1} and I_{d_2} measure the same latent trait ($d = 1, \ldots, q$ and I_d is a subset of $I = 1, \ldots, m$). The general model with *q* dimensions is compared with a restricted version with $q-1$ dimensions, being equal all the other elements of the model, i.e. number of latent classes, type of logit, constraints on item parameters. Similarly (on the basis of LR test), the models with different item discriminating and difficulty parameterizations (constraints) are compared.

The LR test statistic is given by $-2(\hat{l}_0 - \hat{l}_1)$ where $\hat{l}_0$ and $\hat{l}_1$ denote the maximum of log-likelihood of the restricted model and of the general model, respectively. The LR statistic is asymptotically distributed as $\chi^2{}_b$, where *b* is given by the difference in the number of parameters between the two nested models being compared.

3. Empirical analysis

We analyzed ISSP (International Social Survey Programme) data – the public data set, available at *www.diagnoza.com* [see also: Czapiński, Panek (eds.), 2015], using `MultiLCIRT` [Bartolucci, Bacci, Gnaldi, 2016a] package of R.

International Social Survey Programme is a continuing annual programme of cross-national collaboration on surveys covering topics important for social science research a nationally representative. We analyzed the section about workplace flexibility (the willingness and ability to readily respond to changing circumstances and expectations of the unemployed).

The original question was: *In order to get a job I would be willing*:

X_1 (*HSW39_1*) – to accept a job that requires new skills,
X_2 (*HSW39_2*) – to accept a position with lower pay,
X_3 (*HSW39_3*) – to accept temporary employment,
X_4 (*HSW39_4*) – to travel longer to get to work,
X_5 (*HSW39_5*) – to move within country,
X_6 (*HSW39_6*) – to move to a different country.

Each item has five ordered categories: strongly agree (1), agree (2), neither agree nor disagree (3), disagree (4), strongly disagree (5). For the interpretation purposes of the analyses described in the following, the five categories of each item were relabeled[4]. There is complete information on $n = 326$ interviewers who were not currently working for pay[5].

We followed the four ordered steps to proceed to the model selection in LC approach. At the beginning of our analysis, the standard LC model was applied (to select the optimal number s of latent classes). The results of this preliminary fitting for $s = 1 - 8$ are given in Table 2.

[4] We relabeled the original response categories in reverse order (starting with 0-4) for an easier interpretation.

[5] We dropped records with at least one missing responses and "can't choose" category.

Table 2. Log-likelihood, number of parameters, AIC, BIC values for LC models with $s = 1 - 8$

s	LL	npar	BIC	AIC
1	–2488.370	24	5115.626	5024.740
2	–2332.870	49	4949.298	4763.741
3	–2240.317	74	4908.865	4628.634
4	–2150.937	99	**4874.777**	**4499.874**
5	–2178.955	124	5075.485	4605.910
6	–2114.209	149	5090.666	4526.418
7	–2107.126	174	5221.172	4562.252
8	–2111.487	199	5374.567	4620.975

Source: Own calculations in R.

On the basis of the adopted selection criteria, four latent classes was chosen (the smallest estimated BIC and AIC values for $s = 4$ was observed).

In the second step, the LC-IRT models with different link functions were compared. The comparison between a graded response type model and a partial credit type model was carried out (assuming $s = 4$ latent classes, free item discriminating and difficulties parameters and a general multidimensional structure for the data; see: Bacci, Bartolucci, Gnaldi, 2014)[6]. Table 3 shows that a global link has to be preferred to a local logit link function. It can be also observed that a graded response type model has a better fit than the standard LC model (BIC = = 4708.359, AIC = 4575.818 for graded response type model is smaller than for the standard LC model, i.e. BIC = 4874.777, AIC = 4499.874).

Table 3. Graded response and partial credit type models with $s = 4$

Logit	LL	npar	BIC	AIC
Global	–2252.909	35	4708.359	4575.818
Local	–2254.545	35	4711.631	4579.089

Source: Own calculations in R.

In the next step of our analysis, we used an LR test (see Fig. 1) to compare models with different dimensional structure of the latent trait (a graded response model with *m*-dimensional structure and a graded response model with unidimensional structure, i.e. all the items belonging to the same dimension).

[6] The continuation ratio logit link function is not suitable in the context of the empirical study becuase the item response process does not consist of the sequence of successive steps [Bacci, Bartolucci, Gnaldi, 2014].

```
Call:
test_dim(S = S, yv = yv, k = 4, link = 1, disc = 1, difl = 0,
multi1 = cbind(1:ncol(S)))

Testing dimension output:

Log-likelihood of the constrained model   -2252.909
AIC of the constrained model               4575.818
BIC of the constrained model               4708.359
N.parameters of the constrained model        35.000
Log-likelihood of the unconstrained model -2247.213
AIC of the unconstrained model             4584.425
BIC of the unconstrained model             4754.835
N.parameters of the unconstrained model      45.000
Deviance                                     11.393
Degrees of freedom                           10.000
p-value                                       0.328
```

Fig. 1. The test of unidimensionality – the results in R

Source: Own calculations in R.

The results presented at Fig. 1 shows that the hypothesis of unidimensionality cannot be rejected for this data (what seems to be realistic with the context of the study; see: Genge, 2016).

As we mentioned before, the number of the estimated parameters depends on the different constraining imposes (a constant/non-constant discriminating index α_j and of a constant/non-constant threshold difficulty parameter τ_{jx} [7], for each item). In our application, this implies a comparison among four models, in accordance with the classification adopted in Table 1. The parameterization is chosen on account of the unidimensional data structure and the previously selected global logit link function. Besides, because the compared models are nested, the parameterization is selected on the basis of an LR test (Table 4), as well as BIC, AIC criteria (Table 5).

Table 4. Likelihood ratio results for LC graded response models with different item parametrization

Model	LR	npar	p-value
LC-RS-GRM vs LC-GRM	173.8013	15	0.00
LC-1P-GRM vs LC-GRM	130.2626	5	0.00
LC-1P- RS-GRM vs LC-GRM	228.3327	20	0.00

Source: Own calculations in R.

[7] τ_{jx} is known also as a cutoff point between categories.

Table 5. Log-likelihood, AIC and BIC results for different polytomous LC-IRT models

Model	LL	AIC	BIC
LC-GRM	–2252.91	**4575.82**	**4708.36**
LC-RS-GRM	–2339.81	4719.62	4795.36
LC-1P-GRM	–2318.04	4696.08	4809.69
LC-1P-RS-GRM	–2367.08	4764.15	4820.95

Source: Own calculations in R.

Tables 4 and 5 show that LC-GRM has to be preferred among the models considered, i.e. model with a global logit link function, free discriminating and difficulty item parameters, with unidimensional latent trait.

Then, it was of our interest to analyze the distribution of the latent trait based on four ordered latent classes (Table 6), as well as the estimates of the item parameters (Table 7).

Table 6. The estimated support points and prior probabilities for LC-GRM model

Parameter	Cluster 1	Cluster 2	Cluster 3	Cluster 4
ξ_s	3.214	4.037	4.567	10.400
π_s	0.185	0.474	0.329	0.012

Source: Own calculations in R.

On the basis of these results, we conclude that interviewers who were not currently working for pay are mostly represented in the second and third classes, whereas only the 1.2% of the respondents belong to the fourth class.

By examining the estimated, ordered support points we labeled the first group as the least flexible one, and the fourth, which included only 1.2% of the subjects, the most flexible group (ready to accept changes). Furthermore, we examined also the pattern of the conditional probabilities (of the different response categories) to show how it was consistent with what one would expect, based on the labels chosen for the latent classes. The pattern is shown in a graphical depiction in Fig. 2.

We can observe (see Fig. 2) that the probabilities of answering with a high response category (denoting higher level of flexibility skills) increase from class 1 to class 4, whereas the probabilities of answering with a low response category (denoting a lower level of flexibility skills) decrease from class one to class 4.

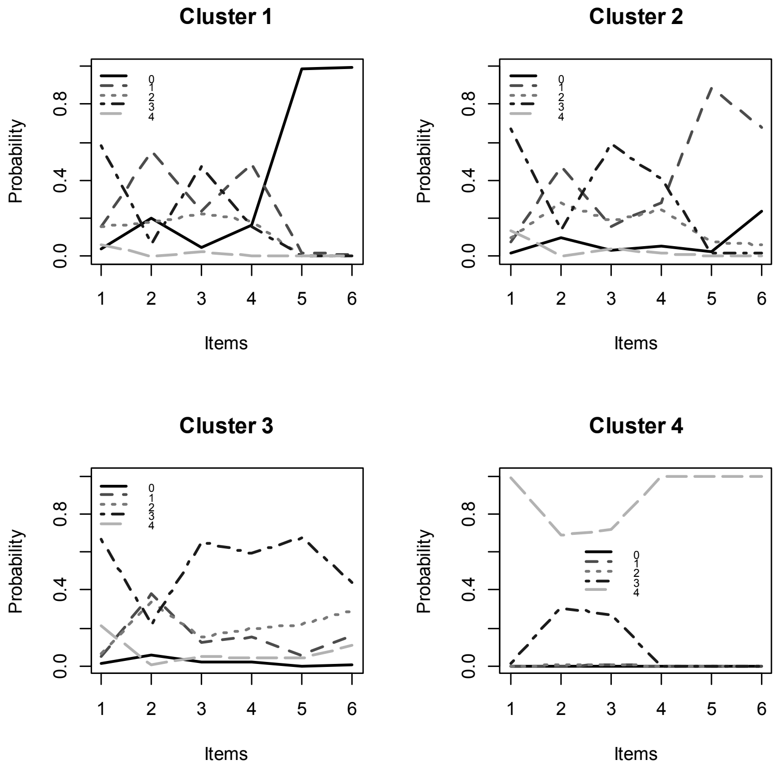

Fig. 2. The conditional probabilities

Source: Own calculations in R.

Then it was also of our interest to analyse also the item parameters under the selected LC-GRM model. The estimates of the item parameters are presented in Table 7 and Fig. 3.

Table 7. The item parameter estimates for LC-GRM model[8]

Item	τ_1	τ_2	τ_3	τ_4	α_j
1	0.000	1.793	2.593	5.894	1.000
2	1.852	4.321	5.787	9.634	1.020
3	–1.295	1.843	3.260	8.968	0.668
4	2.208	3.596	4.227	6.482	1.616
5	3.649	4.275	4.468	4.886	9.497
6	3.884	4.354	4.544	4.844	7.605

Source: Own calculations in R.

8 In order to properly interpret these results, the identifiability constraint adopted in this case is that, for the first item, the discrimination parameter is equal to1 and the first threshold is equal to 0.

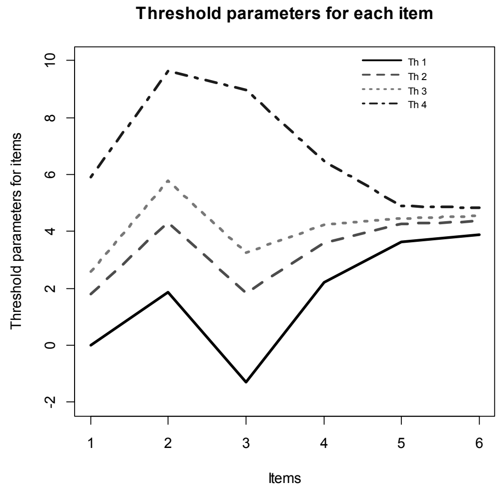

Fig. 3. Threshold parameters for items

Source: Own calculations in R.

On the basis of the Table 7, we conclude that the last two items (concerning the move within or to a different country) have the highest discriminating power. On the other hand, X_3 (the temporary employment) has the lowest discriminating power.

Regarding the threshold parameters (Table 7, Fig. 3), we note that for most of the response categories, the estimates for the sixth and the second items are the highest with respect to the other items, i.e. to accept a move to a different country and a lower pay is the most difficult as opposed to the new skills requirement (the smallest threshold difficulty parameters).

Conclusion

The article presents the approach that combines two types of latent variable models: item response theory models and latent class models. In latent class analysis, the latent variable is discrete and denotes the number of classes in the population. In IRT models the continuous latent variable is used to represent the trait of interest (i.e. ability in certain subjects). The combination of the two mentioned latent variable models concerns the assumption that the population under study is composed by homogeneous classes of individuals who have very similar latent ability levels.

We analyzed the workplace flexibility part of the International Social Survey Programme questionnaire using software of R. According the consecutive ordered steps, we compared different kind of polytomous LC-IRT models (with different number of classes, different types of logit and the constraints on the item parameters, as well as the different dimensional structure). We analyzed the distribution of the latent trait based on four ordered latent classes, as well as the estimates of the item parameters.

This class of models is more flexible in comparison with traditional IRT models, often based on restrictive assumption, such as unidimensionality and normality of latent trait. However, it should be noted that the number of latent dimension choice and items allocation may be confusing (if no a priori information about the dimensionality structure of the questionnaire is given). When the structure of items is not clear (the items cannot be divided between the dimensions, i.e. mathematical and humanistic skills; saving skills for future and current needs), the model-based hierarchical clustering may be performed [Bartolucci, 2007]. This phase should first of all to take into account the interpretability of the dimensions with reference to the specific data set analysis.

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GOTOWOŚĆ DO ZMIAN WARUNKÓW PRACY W POLSCE – ANALIZA Z WYKORZYSTANIEM POLITOMICZNYCH MODELI IRT W PODEJŚCIU MODELOWYM W TAKSONOMII

Streszczenie: Teoria reakcji na pozycję (*item response theory*) zaliczana jest do jednego z dwóch nurtów metodologicznych w ocenie rzetelności skali. Z kolei analizę klas ukrytych (*latent class analysis*) można wpisać w nurt podejścia modelowego w taksonomii, wykorzystujący ideę mieszanek rozkładów. Modele te wykorzystywane są do analizy jakościowych zbiorów danych o niejednorodnej strukturze, w których liczba klas jest nieznana (tzw. zmienna ukryta). W ostatnim czasie na popularności zyskuje podejście modelowe w taksonomii, łączące teorię reakcji na pozycje z modelami klas ukrytych.

W pracy przedstawiono zastosowanie podejścia modelowego w taksonomii wykorzystującego teorię IRT w badaniu umiejętności dostosowania się do zmian polskich respondentów poszukujących pracy. Badania przeprowadzone zostały z wykorzystaniem pakietu `MultiLCIRT` programu R dla danych pochodzących z Międzynarodowego Programu Sondaży Społecznych ISSP 2015.

Słowa kluczowe: teoria IRT, analiza klas ukrytych, podejście modelowe w taksonomii.