Ordinal logistic regression for the analysis of skin test reactivity to common aeroallergens

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Abstract. Clinical research is commonly focused on searching for potential factors and illustrates how they affect a patient's condition. In many epidemiological research studies the response variable is categorical, with more than two categories when there is a natural order among the response categories. In these cases, the ordinal logistic regression models may be employed. In practice, the mostly used type of model is a proportional odds model. The model makes assumptions about the nature of the relationship between the response variable and the prognostic factors. If the proportional odds assumption is violated, generalized ordered logit models may be an option, for example, the partial proportional odds model. The study uses the proportional odds model to examine the dust mite sensitization, whereas the partial proportional model is to examine grass pollen sensitization in children's population. The explanatory variables are: year of a test performance, gender, age and season of birth. The considered models have revealed significant factors that influence dust mite and grass pollen sensitization.

Introduction

Facing an enormous complexity and multidimensional nature of the surrounding reality, it is hard to notice cases when a singular variable describes and explains a particular phenomenon. In the case when we consider more than one explanatory variable, a statistical analysis could be supported by various multiply methods. The application of multiple regression models in medical research has greatly increased in recent years [1–2], especially the use of multiply linear regression for continuous response, logistic regression for binary response, and Cox's proportional hazards model [3] for censored response. These models allow to analyze simultaneously the effect of several explanatory variables on a response variable [1].

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Logistic regression is used to model the binary response variable. Generalization of the logistic regression forms categorical responses with more than two categories. When there is no natural order among the response categories, nominal logistic regression models are used. When response categories are ordered then the logits can utilize the ordering [4]. In many epidemiological studies the response variable is ordinal, for example severity of disease, quality of life in interval scale, health condition indicator [5]. In these cases the ordinal logistic regression models should be employed. This results in models having simpler interpretations and potentially greater power than the nominal logistic regression models.

There are several ordinal logistic models, such as: cumulative logit model, proportional odds model, continuation ratio logit model, adjacent category logit model. Nevertheless, these models have been rarely utilized in biomedical and epidemiological research [5–8].

In practice, the mostly used type of ordinal logistic regression model is the proportional odds model because of the simplicity of its interpretation [1, 4, 8–10]. However, the proportional odds model makes assumptions about the nature of the relationship between the response variable and the prognostic factors. If the proportional odds assumption is violated, the results of this regression can be misleading or have no meaning at all, and generalized ordered logits models are an option. However, the goodness-of-fit verification of regression models is rarely used in medical research [1].

The study applies the proportional odds model for the analysis of the dust mite allergy and partial proportional odds model for a grass pollen allergy.

Ordinal logistic regression

Suppose that response Y has J categories and the probability for category i is given by $P(Y = i) = \pi_i$ for $i = 1, \ldots, J$. Also consider explanatory variables $x_1, \ldots, x_p$. Sometimes, there may be a latent continuous variable Y for which the cutpoints $C_1, \ldots, C_{J-1}$ define J ordinal categories with associated probabilities $\pi_1, \ldots, \pi_J$ (with $\sum_{j=1}^{J} \pi_i = 1$) [10].

A cumulative probability for Y is the probability that Y falls at or below a particular point. For outcome category j, the cumulative probability is $P(Y \leq j) = \pi_1 + \ldots + \pi_j$, $j = 1, \ldots, J$, where $P(Y \leq 1) \leq P(Y \leq 2) \leq \ldots \leq P(Y \leq J) = 1$. The logits of the cumulative probabilities, called cumulative logits, are

$$\log it[P(Y \le j)] = \ln\left[\frac{P(Y \le j)}{1 - P(Y \le j)}\right] = \ln\left[\frac{\pi_1 + \ldots + \pi_j}{\pi_{j+1} + \ldots + \pi_J}\right], \quad j = 1, \ldots, J-1.$$

The cumulative logit model is given by

$$\log it[P(Y \le j)] = \ln\left[\frac{\pi_1 + \ldots + \pi_j}{\pi_{j+1} + \ldots + \pi_J}\right] = \alpha_j + \beta_{j1}x_1 + \ldots + \beta_{jp}x_p, \quad j = 1, \ldots, J-1.$$

If the intercepts α_j depend on the category j, but the other regression coefficients for explanatory variables do not depend on j, then the model is

$$\ln\left[\frac{\pi_1 + \ldots + \pi_j}{\pi_{j+1} + \ldots + \pi_J}\right] = \alpha_j + \beta_1 x_1 + \ldots + \beta_p, \quad j = 1, \ldots, J-1.$$

This is called the proportional odds model. It is based on the assumption that the effects of the covariates $x_1, \ldots, x_p$ are the same for all categories, on the logarithmic scale. The proportional-odds assumption is also called the parallel lines assumption. This assumption must be tested for each covariable separately and in the final model, using for example the Brant test.

When the proportional odds model fits well, it requires a single parameter for x_i rather than $J - 1$ parameters to describe the effect of x_i. If it does not, the partial proportional odds model is recommended [11–12]. This model allows some covariables with the proportional odds assumption to be modelled, but for the covariables failed to perform the proportional odds assumption, it is augmented by a coefficient (γ), which is the effect associated with each j'th cumulative logit, adjusted by the other covariables [9]. In the partial proportional odds model some of the β coefficients can be the same for all categories, while others can differ [13].

Statistics for goodness-of-fit for ordinal regression models are:

1. Chi-square statistic

$$X^2 = \sum_{i=1}^{N} r_i^2 = \frac{(o_i - e_i)^2}{e_i},$$

where $r_i = \frac{o_i - e_i}{\sqrt{e_i}}$ are the Pearson chi-squared residuals; o_i and e_i are the observed and expected frequencies for $i = 1, \ldots, N$; N is J times the number of distinct covariate patterns;

2. Deviance $D = 2[(l(b_{\max}) - l(b)]$, where $l(b)$ is the maximum values of the log-likelihood function for the fitted model and $l(b_{\max})$ is the maximum values of the log-likelihood function for the maximal model;
3. Likelihood ratio chi-square statistic $C = 2[l(b) - l(b_{\min})]$, where $l(b_{\min})$ is the maximum values of the log-likelihood function for the minimal model;
4. Pseudo $R^2 = \dfrac{l(b_{\min}) - l(b)}{l(b_{\min})}$.

If the model fits well then both X^2 and D have, asymptotically, the distribution $\chi^2(N-p)$ where p is the number of parameters estimated. C has the asymptotic distribution $\chi^2[p-(J-1)]$ [10].

A proportional odds model for the analysis of dust mite sensitization in children

The processed data belong to Department of Pediatrics, Gastroenterology and Allergology at the Medical University of Bialystok. Skin prick tests results performed in 2779 children patients were discussed. The population of 1239 patients derives from 1998' and 1540 of them have been diagnosed in 2008'. Skin prick testing was performed using the most common aeroallergens: dust mite and grass pollen. A recorded wheal size for each aeroallergen was treated a desirable result of skin test reactivity. Reactions were considered positive if the wheal was at least 3 mm and was further classified as mild sensitization $\langle 3$ mm, 6 mm), moderate sensitization $\langle 6$ mm, 9 mm), severe sensitization (≥ 9 mm) [14–15]. The results were analyzed separately by: year of a test performance, gender, age, and season of birth. Year of a test performance, gender and age were significantly associated with the degree of skin reactivity to dust mites [Tab. 1]. Gender, age and season of birth were significantly associated with the degree of skin reactivity to grass pollen [Tab. 2].

The study uses the proportional odds model to examine the dust mite sensitization, and next the partial proportional odds model was used to verify the grass pollen sensitization in children's population.

For the first model as a response variable, the dust mite reactivity is classified into four categories: 0 = negative, 1 = mild, 2 = moderate, 3 = severe. A model is constructed using three explanatory variables: year of test performance (1998, 2008), gender (female, male), and a quantitative variable age (in years). The proportional odds model results are shown in [Tab. 3].

Tab. 1. Dust mite sensitization in relation to year, gender, season of birth and age

Co-variable		Dust mite				p-value
		Degree of skin test reactivity				
		Negative n (%)	Mild n (%)	Moderate n (%)	Severe n (%)	
Year	1998 2008	1070 (86.4) 1272 (82.6)	111 (9) 162 (10.5)	40 (3.2) 80 (5.2)	18 (1.4) 26 (1.7)	0.026
Gender	F M	1152 (87.5) 1190 (81.4)	112 (8.5) 161 (11)	39 (2.9) 81 (5.6)	15 (1.1) 29 (2)	0.000
Season of birth	Spring Summer Autumn Winter	643 (84.6) 615 (84.9) 542 (84) 537 (83.3)	72 (9.5) 66 (9.1) 67 (10.4) 68 (10.5)	36 (4.7) 33 (4.6) 25 (3.9) 26 (4)	9 (1.2) 10 (1.4) 11 (1.7) 14 (2.2)	0.885
Age	mean/median	6.9/6	8.8/8	9.3/9.5	10.6/10.5	0.000

Tab. 2. Grass pollen sensitization in relation to year, gender, season of birth and age

Co-variable		Grass pollen				p-value
		Degree of skin test reactivity				
		Negative n (%)	Mild n (%)	Moderate n (%)	Severe n (%)	
Year	1998 2008	1030 (83.1) 1307 (84.8)	144 (11.6) 157 (10.2)	39 (3.2) 56 (3.5)	26 (2.1) 20 (43.5)	0.198
Gender	F M	1146 (87.1) 1191 (81.5)	117 (8.9) 184 (12.6)	39 (2.9) 56 (3.8)	16 (1.1) 30 (2.1)	0.001
Season of birth	Spring Summer Autumn Winter	616 (81.1) 628 (86.7) 552 (85.6) 536 (83.1)	103 (13.5) 67 (9.3) 63 (9.8) 68 (10.5)	31 (4.1) 22 (3) 20 (3.1) 22 (3.4)	10 (1.3) 7 (1) 10 (1.5) 19 (3)	0.019
Age	mean/median	7/6	7.7/7	9.1/8	10.3/10	0.000

The maximum value of the log-likelihood function for the null model is -1593.64 [Tab. 3] and for the fitted model is -1525.09, giving the likelihood ratio chi-squared statistic $C = 137.09$. The p-value for the Likelihood Ratio Chi-Square test (< 0.0001) showing the overall importance of the explanatory variables. All covariates: year, gender and age are found significant [Tab. 3]. That proves all the explanatory variables used in the model have significantly influenced the dust mite sensitization. The positive coefficients for covariates mean that the likelihood of the dust mite sensitization did increase in time, for boys and older children.

Tab. 3. Results of the proportional odds model according to dust mite sensitization

```
Iteration 0:   log likelihood = -1593.6369
Iteration 1:   log likelihood =   -1528.86
Iteration 2:   log likelihood = -1525.0975
Iteration 3:   log likelihood = -1525.0909
Iteration 4:   log likelihood = -1525.0909

Ordered logistic regression                       Number of obs   =       2779
                                                  LR chi2(3)      =     137.09
                                                  Prob > chi2     =     0.0000
Log likelihood = -1525.0909                       Pseudo R2       =     0.0430
```

dust_mite	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
year	.3271335	.1086586	3.01	0.003	.1141666	.5401004
gender	.5897917	.1096038	5.38	0.000	.3749721	.8046112
age	.1227152	.0117304	10.46	0.000	.099724	.1457064
/cut1	3.174464	.1546516			2.871352	3.477575
/cut2	4.306542	.1702723			3.972814	4.640269
/cut3	5.689905	.2153268			5.267872	6.111937

Tab. 4. Odds ratios of the proportional odds model according to dust mite sensitization

dust_mite	Odds Ratio	Std. Err.	z	P>|z|	[95% Conf.	Interval]
year	1.386987	.150708	3.01	0.003	1.120939	1.716179
gender	1.803613	.1976828	5.38	0.000	1.454951	2.235827
age	1.130562	.013262	10.46	0.000	1.104866	1.156857

The proportional odds ratios with the 95% confidence intervals for the ordered logit model are given in [Tab. 4]. For children whose tests were performed in 2008', the odds of a severe skin reactivity to dust mites versus the combined categories such as: moderate, mild or negative skin reactivity are 1.39 (95% CI: 1.12 – 1.72) times greater than for children involved in tests in 1998', given the other variables are held constant in the model. Likewise, for the children of 2008', the odds of severe and moderate skin reactivity to dust mites versus the combined categories: mild and negative skin reactivity are 1.39 (95% CI: 1.12 – 1.72) times greater than for the children of 1998'. For the children of 2008', the odds of positive skin reactivity to dust mites (severe, moderate and mild) versus the negative skin reactivity are 1.39 (95% CI: 1.12 – 1.72) times greater than for the children of 1998'.

For boys, the odds of severe skin reactivity to dust mites versus the combined categories: moderate, mild and negative skin reactivity are 1.8 (95% CI: 1.45 – 2.24) times greater than for girls. Also, for boys, the odds of severe and moderate skin reactivity to dust mites versus the combined categories: mild and negative skin reactivity are 1.8 (95% CI: 1.45 – 2.24) times greater than for girls. For boys, the odds of positive skin reactivity to dust mites (severe, moderate and mild) versus the negative skin reactivity are 1.8 (95% CI: 1.45 – 2.24) times greater than for girls.

For one unit increase in age, the odds of severe skin reactivity to dust mites versus the combined categories like moderate, mild and negative skin reactivity are 1.13 (95% CI: 1.1 – 1.16) times greater. Similarly, for one unit increase in age, the odds of severe and moderate skin reactivity to dust mites versus the combined categories mild and negative skin reactivity are 1.13 (95% CI: 1.1 – 1.16) times greater. For one unit increase in age, the odds of positive skin reactivity to dust mites (severe, moderate and mild) versus the negative skin reactivity are 1.13 (95% CI: 1.1 – 1.16) times greater, given the other variables are held constant in the model.

Brant Test is conducted to check the parallel regression assumption [Tab. 5]. The test yielded $p = 0.455$ indicating that we have not violated the proportional odds assumption and the model is appropriate for this data.

Tab. 5. Brant test of parallel regression assumption for dust mite sensitization

Variable	chi2	p>chi2	df
All	5.73	0.455	6
year	1.82	0.403	2
gender	2.00	0.368	2
age	2.39	0.303	2

The values of the goodness of fit statistics [Tab. 6], the deviance for the fitted model $D = 221$ and the chi-squared statistics $X^2 = 189.99$, compared to the distribution $\chi^2(213)$ indicates that the model provides a good description of the data.

Tab. 6. Goodness of fit statistics

Statistic	Df	Statistic	Statistic/Df
Deviance	213	221	1.037539
Pearson Chi-square	213	189.99	0.891963

A partial proportional odds model for the analysis of grass pollen sensitization in children

Now, as a dependent variable, a grass pollen sensitization inducted wheal size classified into four categories was considered: 0 = negative, 1 = mild, 2 = moderate, 3 = severe. A model was constructed using four explanatory variables: year of test performance (1998, 2008), gender (female,

male), a quantitative variable age (in years) and a variable with more than two categories: season of birth (spring, summer, autumn, winter). For the season of birth variable indicator variables were created, considering summer as a point of references. The proportional odds model results for grass pollen are shown in [Tab. 7].

Tab. 7. Results of the proportional odds model according to grass pollen sensitization

```
Iteration 0:   log likelihood = -1583.2385
Iteration 1:   log likelihood = -1549.3736
Iteration 2:   log likelihood = -1548.5117
Iteration 3:   log likelihood = -1548.5112
Iteration 4:   log likelihood = -1548.5112

Ordered logistic regression                       Number of obs   =       2779
                                                  LR chi2(6)      =      69.45
                                                  Prob > chi2     =     0.0000
Log likelihood = -1548.5112                       Pseudo R2       =     0.0219
```

grass_pollen	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
year	-.117918	.1049732	-1.12	0.261	-.3236616	.0878257
gender	.4702022	.107428	4.38	0.000	.2596472	.6807573
spring	.4547992	.1444034	3.15	0.002	.1717737	.7378247
autumn	.0747166	.1578406	0.47	0.636	-.2346453	.3840786
winter	.339068	.1530095	2.22	0.027	.0391748	.6389612
age	.0777354	.011801	6.59	0.000	.0546059	.1008649
/cut1	2.68902	.1744769			2.347052	3.030988
/cut2	3.972787	.1896236			3.601131	4.344442
/cut3	5.138296	.2258286			4.69568	5.580912

In the beginning the results of Brant test of parallel regression assumption should be performed.

Tab. 8. Brant test of parallel regression assumption for grass pollen sensitization

Estimated coefficients from j-1 binary regressions

	y>0	y>1	y>2
year	-.1170414	-.05456781	-.46217518
gender	.46404076	.46645183	.66521059
spring	.45754732	.36295709	.38360017
autumn	.06959776	.12269193	.42824253
winter	.31704537	.54058301	1.1896764
age	.07345572	.12525583	.16204181
_cons	-2.6501804	-4.4697013	-6.2300726

Brant Test of Parallel Regression Assumption

Variable	chi2	p>chi2	df
All	24.37	0.018	12
year	2.72	0.256	2
gender	0.56	0.757	2
spring	0.19	0.909	2
autumn	0.57	0.751	2
winter	4.11	0.128	2
age	12.79	0.002	2

The Brant test [Tab. 8] yielded p = 0.018, shows that the assumption of the parallel-lines model are violated, but the main problems seem to be with the variable age (p = 0.002). Because the assumptions of the parallel-lines model are violated, the partial proportional model was performed.

Tab. 9. Results of the partial proportional odds model according to grass pollen sensitization

```
Generalized Ordered Logit Estimates                Number of obs   =       2779
                                                   LR chi2(10)     =      92.68
                                                   Prob > chi2     =     0.0000
Log likelihood = -1536.9007                        Pseudo R2       =     0.0293

 ( 1)  [0]spring - [1]spring = 0
 ( 2)  [0]gender - [1]gender = 0
 ( 3)  [0]autumn - [1]autumn = 0
 ( 4)  [0]year - [1]year = 0
 ( 5)  [1]spring - [2]spring = 0
 ( 6)  [1]gender - [2]gender = 0
 ( 7)  [1]autumn - [2]autumn = 0
 ( 8)  [1]year - [2]year = 0
```

grass_pollen	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
0						
year	-.1176639	.1048875	-1.12	0.262	-.3232396	.0879118
gender	.464682	.1072655	4.33	0.000	.2544456	.6749185
spring	.4550394	.144352	3.15	0.002	.1721147	.7379642
autumn	.0736223	.157755	0.47	0.641	-.2355718	.3828163
winter	.3149432	.1531958	2.06	0.040	.014685	.6152013
age	.0730315	.0117847	6.20	0.000	.049934	.096129
_cons	-2.646581	.1738984	-15.22	0.000	-2.987415	-2.305746
1						
year	-.1176639	.1048875	-1.12	0.262	-.3232396	.0879118
gender	.464682	.1072655	4.33	0.000	.2544456	.6749185
spring	.4550394	.144352	3.15	0.002	.1721147	.7379642
autumn	.0736223	.157755	0.47	0.641	-.2355718	.3828163
winter	.5536951	.2113663	2.62	0.009	.1394248	.9679655
age	.133522	.0189941	7.03	0.000	.0962942	.1707498
_cons	-4.529354	.2454247	-18.46	0.000	-5.010377	-4.04833
2						
year	-.1176639	.1048875	-1.12	0.262	-.3232396	.0879118
gender	.464682	.1072655	4.33	0.000	.2544456	.6749185
spring	.4550394	.144352	3.15	0.002	.1721147	.7379642
autumn	.0736223	.157755	0.47	0.641	-.2355718	.3828163
winter	1.147598	.3126305	3.67	0.000	.5348536	1.760343
age	.1808684	.0322675	5.61	0.000	.1176254	.2441115
_cons	-6.376669	.4128261	-15.45	0.000	-7.185793	-5.567545

The partial proportional odds model results are shown in [Tab. 9]. The likelihood ratio chi-squared statistic C = 92.68. The p-value for the Likelihood Ratio Chi-Square test (< 0.0001) showing the overall importance of the explanatory variables. The grass pollen sensitization significantly depends on gender, age, season of birth [Tab. 9]. The year effect is insignificant. The positive coefficients for gender and age mean that the likelihood of the grass pollen sensitization did increase for boys and older children. In Spring born and in Winter born children the likelihood of the grass pollen sensitization increases compared to children born in Summer. In Autumn born children related to Summer born children the seasonal effect is insignificant.

This model is only slightly more difficult to interpret than the earlier proportional odds model. Effects of the constrained variables (year, gender, spring, autumn) can be interpreted much the same as they were previously. For these variables regression coefficients do not depend on response categories. Winter and age variables represent three different regression coefficients per each variable. The coefficients depend on the response categories.

Tab. 10. Odds ratios of the partial proportional odds model according to grass pollen sensitization

grass_pollen	Odds Ratio	Std. Err.	z	P>|z|	[95% Conf.	Interval]
0						
year	.8889948	.0932444	-1.12	0.262	.7238004	1.091892
gender	1.591508	.1707138	4.33	0.000	1.289746	1.963873
spring	1.576236	.2275328	3.15	0.002	1.187814	2.091673
autumn	1.0764	.1698075	0.47	0.641	.7901189	1.466409
winter	1.370181	.209906	2.06	0.040	1.014793	1.850029
age	1.075764	.0126775	6.20	0.000	1.051202	1.100901
1						
year	.8889948	.0932444	-1.12	0.262	.7238004	1.091892
gender	1.591508	.1707138	4.33	0.000	1.289746	1.963873
spring	1.576236	.2275328	3.15	0.002	1.187814	2.091673
autumn	1.0764	.1698075	0.47	0.641	.7901189	1.466409
winter	1.739669	.3677075	2.62	0.009	1.149612	2.632583
age	1.142846	.0217074	7.03	0.000	1.101083	1.186194
2						
year	.8889948	.0932444	-1.12	0.262	.7238004	1.091892
gender	1.591508	.1707138	4.33	0.000	1.289746	1.963873
spring	1.576236	.2275328	3.15	0.002	1.187814	2.091673
autumn	1.0764	.1698075	0.47	0.641	.7901189	1.466409
winter	3.150616	.9849786	3.67	0.000	1.707198	5.814429
age	1.198258	.0386647	5.61	0.000	1.124823	1.276487

For boys, the odds of severe grass pollen sensitization versus the combined categories: moderate, mild and negative are 1.59 (95% CI: 1.29 – 1.96) times greater than for girls [Tab. 10]. Likewise, for boys, the odds of severe and moderate grass pollen sensitization versus the combined mild, negative categories are 1.59 (95% CI: 1.29 – 1.96) times greater than for girls. For boys, the odds of positive skin reactivity to grass pollen (severe, moderate and mild) versus the negative skin reactivity are 1.59 (95% CI: 1.29 – 1.96) times greater than for girls.

For one unit increase in age, the odds of severe grass pollen sensitization versus the combined categories: moderate, mild and negative are 1.08 (95% CI: 1.05 – 1.1) times greater. Also, for one unit increase in age, the odds of severe and moderate skin reactivity to grass pollen versus the combined categories: mild and negative are 1.14 (95% CI: 1.1 – 1.19) times greater.

For one unit increase in age, the odds of positive skin reactivity to grass pollen versus the negative skin reactivity are 1.2 (95% CI: 1.12 – 1.28) times greater, given the other variables are held constant in the model.

In the Spring born group, the odds of grass pollen sensitization versus the combined categories: moderate, mild and negative are 1.58 (95% CI: 1.19 – 2.09) times greater than in the Summer born group. In the Spring born group, the odds of severe and moderate skin reactivity to grass pollen versus the combined categories mild and negative are 1.58 (95% CI: 1.19 – 2.09) times greater than in the Summer born group. In the Spring born children the odds of positive skin reactivity grass pollen versus the negative skin reactivity are 1.58 (95% CI: 1.19 – 2.09) times greater than in the Summer born children.

In the Winter born children, the odds of positive skin reactivity (severe, moderate and mild) to grass pollen versus the negative skin reactivity are 1.37 (95% CI: 1.01 – 1.85) times greater than in the Summer born group. In Winter born group, the odds of severe and moderate grass pollen sensitization versus the combined categories mild and negative are 1.74 (95% CI: 1.15 – 2.63) times greater than in Summer born. In the Winter born group, the odds of severe grass pollen sensitization versus the combined categories: moderate, mild and negative are 3.15 (95% CI: 1.71 – 5.81) times greater than for the children born in Summer.

Conclusions

Before the most popular among ordinal regression models – the proportional odds model is applied, make sure the proportional odds assumption is satisfied. Otherwise, the results can not be credible. If the assumption is not satisfied the generalized logit models (e.g. partial proportional odds model) should be developed. Application of the ordinal logistic regression models lets us reveal the critical factors that influence dust mite and grass pollen sensitization. In the dust mite case these factors are: year of a test performance, gender and age. In the grass pollen case we find gender, age and year of a test performance significant.

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