2014•2015
FACULTY OF SCIENCES
Master of Statistics

Master's thesis
Belgian teachers' perception on gifted children

Supervisor :
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Hiwot Garedew Zeleke

Thesis presented in fulfillment of the requirements for the degree of Master of Statistics

Transnational University Limburg is a unique collaboration of two universities in two countries:
the University of Hasselt and Maastricht University.

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Abstract

Giftedness in young children, can be seen in their exceptional performance on tests and/or other measures of ability (such as Intelligence Quotient (IQ)) or as a rapid rate of learning, compared to other students of the same age. Given that teachers have one of the most significant influences on the educational development of gifted children, the goal of this thesis was to look at the baseline characteristics (pre-training) of 506 Belgian teachers (184 pre-school, 261 primary school and 61 remedial teachers) on their knowledge, experience and opinion about gifted children. Different model which takes into account the ordinality of the response were fitted, such as: Log-linear model (Linear by linear association), proportional odds model (POM), and partial proportional odds model (PPOM) in order to address the research questions.

Association between Knowledge and Experience was observed in educational adaptation for gifted children. There is some difference among functions (pre-school, primary school and remedial teachers) in responding related to knowledge, opinion and concern and specific knowledge for differentiation and acceleration. Teaching experience and care experience teachers have some significant effects on teachers' opinion and concerns and specific knowledge for gifted children.
Key words: POM, PPOM, Linear by Linear, OR

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Contents

1 Introduction

Gifted individuals are those who demonstrate outstanding levels of aptitude (defined as an exceptional ability to reason and learn) or competence in one or more domains (eg. mathematics, music, language, arts). In young children, giftedness can be seen in their exceptional performance on tests and/or other measures of ability or as a rapid rate of learning, compared to other students of the same age. It is essential to realize that although they share the same basic needs as other children, gifted children need very different nurturing and educational needs. In order therefore to effectively support their development and appropriate educational programs, proper identification of gifted children is important.

Numerous old studies have confirmed that moderately gifted individuals tend to do well in school and to achieve success in later life (for example Gallagher, 1975). In this regard, Roedell (1984) claims that there is a consensus that gifted children are more susceptible to some types of developmental difficulties than are moderately gifted or average children. She identifies the common areas of vulnerability as uneven development, perfectionism, adult expectations, intense sensitivity, self-definition, alienation, inappropriate environments, and role conflicts.

In addition, literature studies and practice in the field shows that school related problems, such as a bad study habits, boredom and underachievement are common among the gifted children (Gulah et al., 2013). This is because the classical educational programs are oriented towards average pupils, and do not accommodate the more advanced gifted learners in the classrooms. However, gifted children have special learning and social-emotional needs, and require a differentiated curriculum with an optimal learning environment (Chan, 2001). Related with this, one of the important issues to consider in gifted children education is characteristics and competencies of teachers. In this regard, Feldhusen (1997) identifies being highly intelligent, achievement oriented, knowledgeable and flexible; having cultural and intellectual interests; respecting individual differences; and relating well with gifted individuals as some of the main characteristics that needs to be exhibited by teachers.

Given that teachers have one of the most significant influences on the educational development of gifted students, it is important to understand teachers' attitudes and beliefs in order to implement effective training and educational practices to improve education for gifted students. Lack of knowledge and understanding (from lack of training) are believed to be a main cause of mistaken beliefs and negative attitudes among teachers (Clark, 2002). And teachers are only as effective with gifted students as they are knowledgeable about how to work with gifted students (Lassig et al., 2009).

In order to accommodate the more advanced, gifted learners in the classroom, Exentra VZW in Belgium, developed a multi-annual, in-depth training program for school personnel and parents. The focus of the program is to provide the necessary training on how to recognize the gifted children and how to successfully implement a challenging education environment for gifted children in regular Belgian schools. To assess the effectiveness of this program, a survey was performed on different Belgian schools which have undergone training. The goal of this thesis is to look at the baseline characteristics (pre-training) of teachers in pre-school, primary school and remedial teachers. Specifically, the aim is to investigate:

1. Correlation between the degree of experience and the degree of knowledge of teachers with educational adaptations for gifted children.
2. Difference in the level of knowledge and experience with educational adaptations between the different functions(pre-school, primary school and remedial school) with and without taking the the demographic variables in to consideration.
3. Difference among functions on responses related to opinion and specific knowledge (differentiation and acceleration) of a teachers with and without taking the demographic variables in to account.

1.1 Data and Survey Methods

The cross sectional data was collected from a survey which was performed at 30 Belgian schools. A total of 506 teachers (184 pre-school teachers, 261 primary school teachers, and 61 remedial teachers) were asked to fill electronic questionnaire containing questions with regards to their perception on gifted children. The datasets also contains the demographic characteristic of the respondents such as: years of teaching experience($Experience\_teaching$), years of experience as a care teacher($Experience\_care$), teachers type($Function$), and class taught ($class$). For the remedial teachers only the years of teaching experience and years of experience as care teacher were available. Table 1 below displays description of the demographic characteristics of the respondents and in teacher can teach more than one classes.

Table 1: Descriptions of baseline characteristics

Variable		class	lable	number	Discription
Function	Pre-scool	0	Yes	56	Pre-nursery class teacher
		1	Yes	80	First nursery class teacher
		2	Yes	77	Second nursery class teacher
		3	Yes	79	Third nursery class teacher
	Primary school	1	Yes	58	First lower school class teacher
		2	Yes	46	Second lower school class teacher
		3	Yes	49	Third lower school class teacher
		4	Yes	45	Fourth lower school class teacher
		5	Yes	46	Fifth lower school class teacher
		6	Yes	45	Sixth lower school class teacher
	Remedial techerteachers			61	Support and care teacher
Experience_teaching					Number of years of teaching experience(in year)
Experience_care					Number of years of experience as a care teacher(in year)

The covariate *Function* categorized as follows.

$$Function = \begin{cases} 1 = Pre\_school\ teachers \\ 2 = Pimary\ school\ teacher \\ 3 = Remedial\ teacher \end{cases}$$

A *Class* covariate was also categorized into 6 categories as follows so that we will be able to make comparison between classes in the primary school only. Hence, some teacher in primary school teachs more than one class, for the simplicity of analysis we consider the highest class i.e. if one teacher teach in class 1, 2 and 3 we consider class 3 only.

$$class = \begin{cases} 1 = Primary\ teacher\ in\ class\ 1 \\ 2 = Primary\ teacher\ in\ class\ 2 \\ 3 = Primary\ teacher\ in\ class\ 3 \\ 4 = Primary\ teacher\ in\ class\ 4 \\ 5 = Primary\ teacher\ in\ class\ 5 \\ 6 = Primary\ teacher\ in\ class\ 6 \end{cases}$$

The 40 response variables of interest and their descriptions are given in Appendix Table16. All responses consists of ordinal levels. Table 2 below summarizes reponse type and their levels. Questions about knowledge and experience for educational adaptations, opinion and concerns, and specific knowledge for acceleration were asked to all teachers (pre-school, primary school, and remedial teachers), while questions about specific knowledge for differentiation for pre_school and primary school teachers were different i.e the first 7 responses were asked to only primary school and remedial teachers, the next 7 was asked to pre-school and remedial teachers only and the last 3 were asked to all teachers (pre, primary and remedial teachers).

Table 2: Response type and levels

Response Type	No. of response	Level
Educational Adaptations	2	1=not, 2=to a lesser extend, 3=to a large extend
Opinion and Concern	17	1=strongly disagree, 2=slightly disagree, 3=neutral, 4=slightly agree, 5=strongly agree
Differentiation	17	1=strongly disagree, 2=slightly disagree, 3=neutral, 4=slightly agree
Acceleration	4	2=disagree, 3=neutral, 4=agree

2 Statistical Methodology

The types of model for data analysis highly depends on the nature and measurement scale of the outcome variables. The level of outcome of the variable of interest is ordinal in this study. Ordinal data are a specific form of categorical data, where the order of the categories is of importance. Log-linear model and models that use cumulative probabilities like proportional odds models, adjacent categories logits and continuation ratio logits (Agresti, 2002) are possible choices for modelling ordinal data. Continuation-ratio model is suited when the underlying outcome is irreversible in the sense that upon attaining a certain level of one outcome, subjects response cannot revert to a lower level and adjacent-category model designed for situations in which the subject must pass through one category to reach the next category (Liu et al, 2005) are not used in this analysis.

2.1 Log-linear Model

Log linear models can be used to analyze the relationship between two or more categorical variables. The variables investigated by log linear models are all treated as response variables. In other words, no distinction is made between independent and dependent variables. Log linear analysis is an extension of the two-way contingency table where the relationship between two or more categorical variables is analyzed by taking the natural logarithm of the cell frequencies within a contingency table (Agresti, 2002). We applied this log-linear model, since one of the main goal of this study was to determine the association between two responses ($Knowledge$ and $Experience$) in educational adaptations for gifted children. The log-linear Linear by Linear association model that was used for ordinal association is formulated as below.
Given scores for the rows $u_1 \leq u_2 \leq u_3$ and scores for the columns $v_1 \leq v_2 \leq v_3$, then we can model the dependence between the variables.

$$log(\mu_{ij}) = \lambda + \lambda_i^{Knowledge} + \lambda_j^{Experieance} + \beta(u_i v_j) \quad for\ (i, j = 1, 2, 3)$$

Where μ_{ij} is the expected cell frequency of the cases for cell ij in the contingency table, λ is the overall mean of the natural log of the expected frequencies, $\lambda_i^{Knowledge}$ is the main effects for variable Knowledge, $\lambda_j^{Experience}$ is the main effects for variable Experience, β is the regression coefficient for association, and u_i and v_j are score for each category of Knowledge and Experience respectively. The direction and strength of the association depends on β, if $\beta > 0$ then Knowledge and Experience are positively associated (i.e. Knowledge tends to go up as Experience goes up and vice versa) and if $\beta < 0$ then Knowledge and Experience are negatively associated. It is called Linear by linear association model because for each row i , the association is a linear function of the columns ($\lambda_{ij}^{Experieance*Knowledge} = (\beta u_i)v_j$) and for each column j , the association is a linear function of the rows ($\lambda_{ij}^{Experieance*Knowledge} = (\beta v_j)u_i$) (Agresti, 2002).

2.2 Proportional odds Model (POM)

Proportional odds model is also a sensible choice for the ordinal outcomes, as it is an extension of binary logistic regression, it is sometimes referred to as the ordinal logistic model; because it is defined by the log-odds of the cumulative probabilities, it is also referred to as a cumulative odds model. The unique feature of proportional odds model is that the odds ratio for each predictor is taken to be constant across all level of the response variable. When the proportional odds assumption is met, odds ratios in a proportional odds model are interpreted as the odds of being lower or higher on the outcome variable across the entire range of the outcome (Susan C. et al, 1997). We fitted this model by using the responses of the teacher in different questions as dependent variable, with *Function*, *Experience_teaching*, *Experience_care*, and the interaction between *Experience_teaching* and *Experience_care* as explanatory variables. The model is formulated as below and it assumes an identical effect of the predictors for each cumulative probability:

$$\log \frac{P(Y_i \le k)}{P(Y_i > k)} = \alpha_k + \beta_{1j} * Function_i + \beta_2 * Experience\_teaching_i + \beta_3 * Experience\_care_i$$
$$+\beta_4 * Experience\_teaching_i * Experience\_care_i$$

Where: Y_i is the response of the i^{th} teacher (i=1,2...,n) and k is the level of the ordinal response (k = 1, 2,...,K). The coefficient α_k is the intercept for the k^{th} cumulative odds model and is usually considered as nuisance parameter of little interest (Agresti, 2002). The parameters β_{1j} (j=1,2) is the effect of Function$_i$ and β_2, β_3 and β_4 is the effect of Experience_teaching, Experience_care and the interaction between Experience_teaching and Experience_care respectively.

2.3 Partial proportional odds model (PPOM)

When the proportional odds assumption applies to some but not all of the covariates, partial proportional odds model can be used. Partial proportional odds refers to the case that at least one of the slopes for an explanatory variable varies across level of the response (O'Connell et al, 2011). The same model formulation can be used in the above proportional odds model, but later we will give different slope after identifying covariates that requires different slopes.

2.4 Comparison among functions

To test for differences among $Functions$ the Likelihood Ratio Test was used with the following hypothesis:

$$H_0 : \beta_{11} = \beta_{12} = 0$$

$$H_a : Not\ all\ \beta_{1j}\ are\ equal :\ for\ j = 1, 2, 3$$

In case of a significant effect of function, the hypothesis to test the pairwise difference between each levels of function are:

- function1 (pre-school teacher) versus function3 (remedial teachers)
  $H_0 : \beta_{11} = 0$, $H_A : \beta_{11} \neq 0$
- function2 (primary school teacher) versus function3 (remedial teachers)
  $H_0 : \beta_{12} = 0$, $H_A : \beta_{12} \neq 0$
- function1 (pre-school teacher) and function2 (primary school teacher)
  $H_0 : \beta_{11} = \beta_{12}$, $H_A : \beta_{11} \neq \beta_{12}$

2.5 Likelihood Ratio Test(LRT)

Likelihood ratio tests (LRT) is the most popular test used to compare two nested models and to test the the fixed parameters in the model. The test is calculated by subtracting the value of -2*loglikelihood associated with full model from that of the reduced (nested to the full) model. Under some regularity conditions, asymptotically the test statistic is distributed as a chi-squared random variable, with degrees of freedom equal to the difference in the number of parameters between the two models (Verbeke and Molenberghs, 2000).

2.6 Statistical software used

Data manipulation and exploratory data analysis was performed using SAS version 9.4 and R version 3.1.2. The POM and PPOM were fitted using PROC LOGISTIC and PROC GENMOD procedures. All hypotheses were tested at 5% significance level. The codes for data manipulations and analysis presented in the Appendix.

3 Result

3.1 Exploratory Data Analysis

In order to get an insight into the data structure, some summary statistics and graphical techniques (bar charts and mosaic plot) were used.
Table 3 below summarizes frequency of pre-school, primary school and remedial teachers knowledge and experience for educational adaptation and specific knowledge for acceleration of gifted children. About 91% of teachers (342 to a lesser extent and 123 to a large extent out of 506) and 87.55% (362 to a lesser extent and 81 to a larger out of 506) have knowledge and experience about educational adaptation respectively. About 68% (345 teachers) of the teachers have a positive opinion in favor of accelerating gifted children.

From Table 4 below that contain frequency of response related to teachers opinion and concerns, we can see that around 52% of teachers agree (197 teachers for slightly agree and 67 teachers strongly agree)on it is difficult to detect which children need more challenge at school while 39.92% teachers disagree (35 teachers strongly disagree and 167 teachers slightly disagree). Around 40% of the respondent agree (169 teachers strongly agree and 36 slightly agree) that they are not confident enough to apply educational adaptations for gifted children while around 53% disagree (64 strongly and 203 slightly disagree.) The remaining responses can be interpreted similarly.

Table 5 frequency of response related to specific knowledge of differentiation for gifted children for primary school and remedial teachers only. About 44% of the teachers (144 teachers) from the primary school and remedial, have slightly positive responses to continue to offer challenging exercises, even if the child does not want to make them or gets frustrated while 49.69% of them disagree (14 teachers strongly and 146 slightly disagree). On the other hand, only 22% of the respondents (72 teachers) agree on offering more of the same (basic) exercise, when the gifted child with its basis assignments while around 68% (222 teachers) disagreed.

Table 6 summarizes the frequency of teachers' response about specific knowledge of differentiation for gifted children for pre-school and remedial teachers only, is interpreted as in Table 5.

The average teaching experience for all types of teachers (function) was 17 years with standard deviation 10.4272 years, ranging from no experience (0 years) and to 38 years of experience.

The mean and standard deviation of experience as a care teacher for remedial teachers were 4.5577 and 4.2214 respectively, ranging from 0 to 15 years.

Table 3: Frequency of teachers' response in terms of educational adaptations and accelerations

Category	Response	Not	To a lesser extent	To a large extent	Missing
Educational adaptation	Knowledge	29	342	123	12
	Experience	47	362	81	16
		Disagree	Nuetral	Agree	Skipped
Acceleration	Accelleration	141	20	345	
	Opinion_child_accell	182	11	173	140
	Catch_up_accell	160	65	155	126
	Gap_accell	205	27	89	185

where: Opinion_child_accell=Opinion child accelleration, Catch_up_accell=Catch up accelleleration

Table 4: Frequency of teachers' response in terms of opinion and concern about gifted children

Response	Strongly disagree	Slightly disagree	Nuetral	Slightly agree	Strongly agree
Difficult_to_detect	35	167	40	197	67
Not_confident	64	203	34	169	36
Overburdened	246	188	23	42	7
Fear_of_failure	114	219	38	114	21
Being_a_child	127	168	25	168	49
Outside_of_school	250	149	27	57	23
Parents_pressure	122	41	33	129	122
Collegues_not_open	194	163	26	93	30
Resources_weaker_children	175	153	61	90	27
Long_term_effect	308	159	19	10	10
Vain	73	257	68	93	15
Not_feasible_differentiation	66	139	36	186	82
Extra_time_differentiation	30	131	47	203	95
Less_time_differentiation	46	67	51	178	67
Ache_for_differentiation	142	32	32	117	32
Selfesteem_pullout	153	190	59	89	15
Convinced_benefit	17		25		464

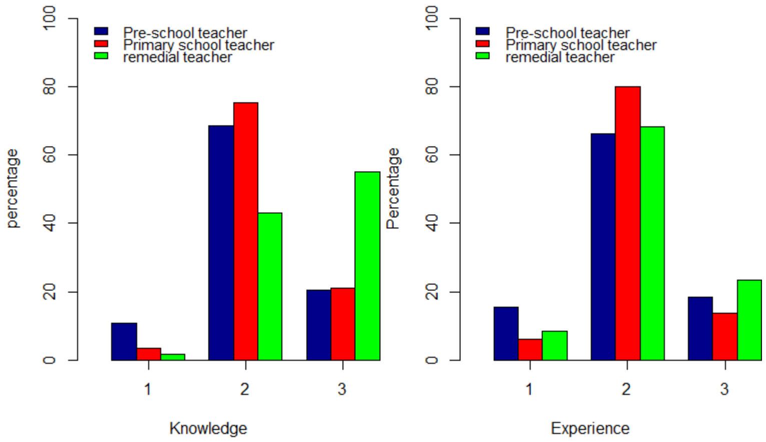
Table 5: Frequency of primary school and remedial teachers' response for specific knowledge (differentiation)

Response	Strongly disagree	Slightly disagree	Nuetral	Slightly agree
Not_want_diff_continu	14	146	18	144
Many_mistakes_diff_continue	49	119	20	134
Working_attitude_diff_continu	46	120	16	140
	Disagree	Nuetral	Agree	
Extra_basic_diff_primaryschool	222	16	72	
Nice_to_have_diff_primaryschool	197	17	96	
Same_assignments_diff_primarysch	194	0	104	
Choose_diff_primaryschool	224	27	59	
Eliminate_diff_primaryschool	84	18	208	
Challenging_diff_primaryschool	42	15	25	
Mandatory_diff_primaryschool	196	24	90	

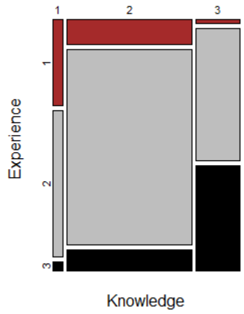
Table 6: Frequency of pre-school and remedial teachers' response for specific knowledge (differentiation)

Response	Strongly disagree	Slightly disagree	Nuetral	Slightly agree
Not_want_diff_continu	7	128	14	96
Many_mistakes_diff_continue	42	85	11	107
Working_attitude_diff_continu	33	115	11	86
	Disagree	Nuetral	Agree	
Extra_basic_diff_preschool	15	6	199	
Nice_to_have_diff_preschool	70	19	131	
Same_assignments_diff_preschool	210	7	3	
Choose_diff_preschool	52	27	141	
Eliminate_diff_preschool	129	16	75	
Challenging_diff_preschool	13	9	198	
Mandatory_diff_preschool	149	10	61	

One of the interests in this study is to look at differences between Functions. From the bar charts in Figure 1a (the left panel) there seems to be a considerable difference between functions in both responses of knowledge and experience for educational adaptation. The mosaic chart in Figure1b (right panel) visually shows the two way distribution of experience and knowledge. It depicts the agreement between having experience and knowledge for educational adaptation. Chi-squared test for independence was used to get an insight about the associations between experience and knowledge for educational adaptations and a significant test result were found (p_value = 0.001). But like some significance test, chi-square tests of independence have limited usefulness. A small p-value indicates strong evidence of association but provides little information about the nature or strength of the association (Agresti, 2002). In order to overcome some of the gaps that could not be answered by chi-square test of independence log linear model was fitted and the results are discussed in the next sections (section 3.2).



(a)



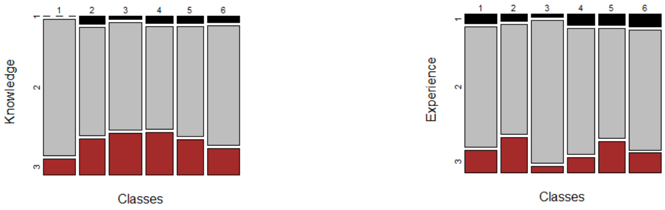
(b)

Figure 1: Distribution of teachers' response for Knowledge and Experience in educational adaptation

Where: Figure (a) a bar chart by Function, while (b) shows a mosaic plot for the proportion of Experience vs Knowledge. The x-axis label for (a) and column and raw names for (b) is coded as follows:1= not, 2= to a lesser extent and 3= to a large extent.

Mosaic plots displayed in Figure 2a and 2b below, shows the association between Knowledge with each classes and Experience with each class of primary school teachers respectively. The plot shows similarity of response between classes, where for both response (knowledge and experience) most primary teachers in all classes chose to a lesser extent followed by to a large extent. On the other hand, different between classes can be observed for $Convinced\_benefit$, $Difficult\_to\_detect$, $Same\_assignments\_diff\_primarysch$ and $Choose\_diff\_primaryschool$ (Figure 3). A formal test needs to be applied in order to confirm these similarities/differences.

Appendix Figures 6, 8 and 9 displays bar charts of different responses versus functions. From these Figures there seems to be a difference between functions for each response variable which are related to teachers opinion and concerns, specific knowledge for differentiation and acceleration for gifted children. The observed differences between the levels of function shown by the bar charts will be confirmed by fitting proportional odds models and partial proportional odds models.



(a) (b)

Figure 2: Mosaic plot of (a) Knowledge (b) Experience in each class of primary school
The row names shows the different response category: 1= not, 2= to a lesser extent, 3= to a large extent, while the columns corresponds to the different class level (first lower school class teacher, second lower school class teacher,...,six lower class school teacher).

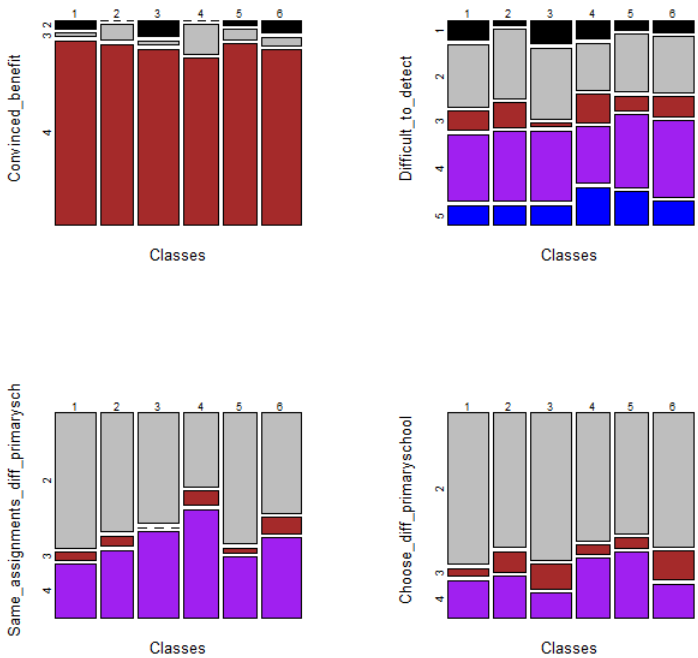


Figure 3: Mosaic plot of selected responses in each class of primary school

3.2 Log-linear model

In this section, we fitted a log linear model Linear by Linear association in order to assess the association between teachers' knowledge and experience for educational adaptation to gifted children. One of the assumptions when using log-linear model is that the number of observation is large. For this assumption to hold, we checked that the expected frequencies are greater than or equal to 5 for 80% or more of the categories and all expected frequencies is greater than one (Howell, 2009).

The Goodness-of-fit tests displayed in Table 7 shows that the model of independence is inadequate, and a Linear by Linear association model fits the data well.

Table 7: Goodness-of-Fit of Log-linear Models

Test	DF	LTR(G^2)	P_ Value
H_0:Independent	4	87.28	<.0001
H_A :Not independent			
H_0 :L by L Association	3	2.17	0.5399
H_A :Not Linear By Linear			

where: L by L is linear by linear accoiation model , LTR is Likelihood Ratio Test

Table 8 below contains the estimate and standard deviation for each level of the variable and for the association based on linear by linear association model. Testing whether there is an association between Knowledge and Experience(H_0: β=0), based on Likelihood Ratio test(G^2 = 85.11 (87.28-2.17) with 1 df, p_value< 0.0001) we rejected the null hypothesis, indicating that there is positive association (β=1.1859) between knowledge and experience in educational adaptation for gifted children. Teachers having experience to a large extent tend to have knowledge to a larger extent. The strongest association occurs in largest differences between scores and the smallest associations occur for rows and columns that have scores that are more nearly equal. The odds of having experience in applying educational adaptations for gifted children to a larger extent versus not, if you have knowledge about educational adaptation to a larger extent is exp(1.1859*(3-1)(3-1))=114.8469 times the odds of having no knowledge.

Table 8: Parameter estimates and p-values for linear by Linear association model

Parameter		DF	Estimate	Standard Error	P_value
Intercept		1	1.1806	0.2089	< .0001
experience	To a large extent	1	-3.6774	0.7505	< .0001
experience	To a lesser extent	1	-0.0422	0.3609	0.9068
knowledge	To a large extent	1	-4.4241	0.7914	< .0001
knowledge	To a lesser extent	1	-0.3346	0.3688	0.3642
β		1	1.1859	0.1812	< .0001

3.3 Proportional odds model and Partial Proportional odds model

3.3.1 Kowledge and Experience for educational adaptations

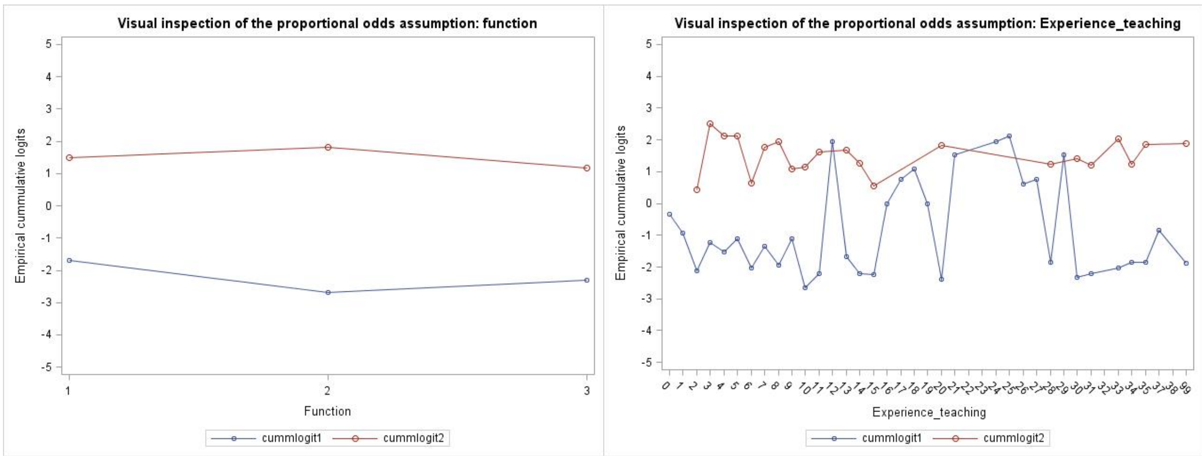
The Deviance and Pearson statistics were used to test the goodness-of-fit of the fitted models, and the result shown in Table 9 indicates that both models (Model1 Knowledge as a response and Model2 Experience as a response) fitted the data well since the ratio of the statistics to the degrees of freedom were closer to 1 and the hypothesis that the fitted models are correct was not rejected (p_value=0.9646 and 0.2126 respectively). Another issue of modeling proportional odds model was the assumption of equal slopes of the predictors, across the two models. The assumption was tested using score statistics, this assumption was not violated for model1 only, i.e. the hypothesis that the slopes are equal was not rejected at 5% level of significance ($\chi^2(5)$=8.4763 with p_value w=0.1319) but it was not the case for model2 since p_value was 0.0032.

Table 9: Deviance and Pearson Goodness-of-Fit Statistics

	Criterion	Value	DF	Value/DF	P-value
Model1	Deviance	60.2905	63	0.9569	0.5735
	Pearson	59.4486	63	0.9436	0.6036
Model2	Deviance	73.8012	65	1.1354	0.2126
	Pearson	71.7276	65	1.1035	0.2647

where:Model1 is for Knowledge response, Model2 for Experienace response

Due to the violation of this assumption for model2, drawing valid inference based on parameter estimates may not be valid. Empirical cumulative logit plots were used in order to identify the covariate that requires different slopes. Recall that, if the plots of the resulting fitted cumulative logits are not parallel for specific covariate, then this provides requiring different slopes. From Figure 4b below covariate *Experience_teaching* (right panel) and Figure 5 covariate *Experience_care* line was not parallel for each cumulative levels of response *Experience* (Model2), which suggests that we need to relax these two covariates only by giving different slopes.



(a) (b)

Figure 4: visual inspection of the proportional odds assumption (a)Experience versus Function (b)Experience versus Experience_teaching

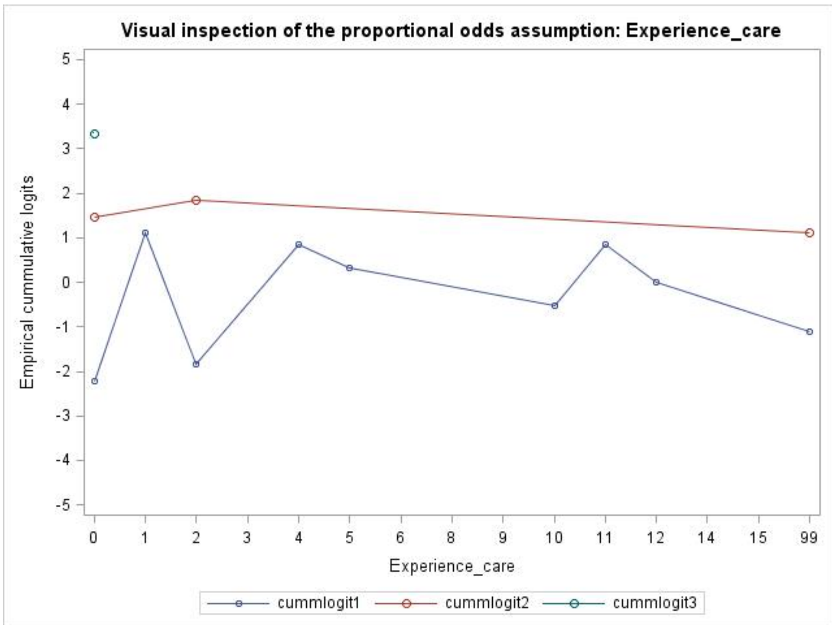


Figure 5: visual inspection of the proportional odds assumption for Experience versus Experience_care.

For both Knowledge and Experience model, the probabilities modeled are summed over the responses having the higher ordered values in the response i.e. in the direction of **to a large extent, to a lesser extent and not** ($\log \frac{P(Y_i \geq k)}{P(Y_i < k)}$). Based on information obtained from the emperical logit plots, the PPOM for response Experience reformulated as bellow by allowing the effect of $Experience\_teaching$ and $Experience\_care$ to vary across the response category levels, while the effects of $Function$ and the interaction between $Experience\_teaching$ and $Experience\_care$ fixed at each category as done in POM.

$$\log \frac{P(Y_i \geq k)}{P(Y_i < k)} = \alpha_k + \beta_{1j} * Function_i + \beta_{2k} * Experience\_teaching_i + \beta_{3k} * Experience\_care_i$$
$$+ \beta_4 * Experience\_teaching_i * Experience\_care_i$$

Where Y_i is the response on Experience for educational adaptation for gifted children of the i^{th} teacher, β_{2k} and β_{3k} measure the log odds effect of $Experieance\_teaching$ and $Experieance\_care$ at k^{th} category level of the outcome respectively. The remaining parameters have the same definition with the POM.

Table 17 in Appendix, contains the likelihood ratio test for testing differences between functions on Experience and knowledge for educational adaptations. We observed significant difference among functions (pre-school, primary school and remedial school teachers) with and without taking the demographic characteristic in to considerations for knowledge for educational adaptations since Likelihood Ratio test p_value for both is <.0001. This indicates that we reject the null hypothesis testing that all functions are equal (β_{11}=β_{12}=0). While only significant difference among function was observed for experience without taking the covariate in to account (p_value =0.0084). This shows, having teaching and care experience makes all teachers to have similar experience for educational adaptation.

Table 10 below contains, the Parameter estimates and standard deviation with and without covariates for both Model1(POM) and Model2(PPOM).

In Model1, looking at pair-wise comparison we found only a significant difference between $function1$ with $function3$ and $function2$ with $functon3$ (p_value 0.0001 and 0.0001 respectively). The odds of having knowledge to a large extent versus to the other category for teachers in pre_school was found exp(-0.7676)= 0.464 times remedial teachers in educational adaptation for gifted children , given that $Experience\_teaching$, $Experience\_care$ and their interaction were held constant. Similarly, for teachers in primary school group, the odds of having knowledge to a large extent versus to the other category was found to be exp(-0.4798) = 0.632 times remedial teachers for educational adaptation for gifted children , given that the other covariate held constant. On the other hand the interpretations of the slope parameters for the odd of having knowledge to a lesser extent or to a large extent versus not having knowledge is exactly the same with the parameters we used to interpret the odds of having knowledge to a large extent in the previous statements. This is because we used common slope parameters for functions. From these results we can see that, the probability of having knowledge to a large extent is higher for remedial school teachers and it is lower for pre-school teachers. Regarding interaction between *Experience_teaching* and *Experience_care* we found significant effect on knowledge (p_value=0.0187), which implies that the effect of care experience depends on teaching experience on having knowledge on educational adaptation for gifted children.

In Model2 (Experience as response), no statistical significant difference was observed among function (with and without taking the other covariate in to considerations) in having experience in educational adaptation for gifted children. Since the covariate *Experience_teaching* vary across the level of responses, but only one level of this slope was found to be significant, the cumulative odds ratio of about 1.033 (exp(0.0334) p_value =0.0187) suggesting that the odds of a teachers having experience for educational adaptation to a large extent or having to a lesser extent versus not having experieance for educational adaptation increases by approximately 3% for a 1 year increase in teaching experience given that the other covariates are held fixed. This indicates that an increase in teaching experience (in years) is related to increasing having experience for educational adaptation. Significant effect of interaction between *Experience_teaching* and *Experience_care*, implies that the effect of experience as a care teacher depends on teaching experience on having experience on educational adaptation for gifted children.

Table 10: Parameter estimates and Standard deviation for model with and without (only function) covariates for responses Knowledge and Experience

			With covariate			Without Covariate		
Model	Effect	Parameter	Estimate	SE	P_Value	Estimate	SE	P_value
Model1	Intercept(3)	α_3	-0.8829	0.1706	$< .0001*$	-3.2486	0.2152	$< .0001*$
	Intercept(2)	α_2	3.1915	0.2380	$< .0001*$	0.8287	0.1228	$< .0001*$
	Function(1)	β_{11}	-0.7926	0.1635	$< .0001*$	0.7093	0.1570	$< .0001*$
	Function(2)	β_{12}	-0.4586	0.1491	0.0021*	0.4287	0.1424	0.0026*
	Experience_teaching	β_2	0.00606	0.00535	0.2574			
	Experience_care	β_3	0.00252	0.0124	0.8393			
	Exp_care_teaching	β_4	0.0005	0.00023	0.0187*			
$Model2^a$	Intercept(3)	α_3	-1.5121	0.2034	$< .0001*$	-2.3545	0.1737	$< .0001*$
	Intercept(2)	α_2	1.8178	0.2744	$< .0001*$	1.5248	0.1365	$< .0001*$
	Function(1)	β_{11}	-0.2626	0.1694	0.1211	0.2694	0.1600	0.0092*
	Function(2)	β_{12}	-0.0644	0.1541	0.6763	0.0819	0.1467	0.5765
	Experience_teaching(3)	β_{23}	0.0021	0.00735	0.7754			
	Experience_teaching(2)	β_{22}	0.0334	0.0142	0.0187*			
	Experience_care(3)	β_{33}	0.0196	0.0124	0.1145			
	Experience_care(2)	β_{32}	0.00628	0.0170	0.7115			
	Exp_care_teaching	β_4	0.00063	0.0003	0.0249*			

Where: Model1 is with Knowledge reponse, $Model2^a$ Experience response is modeled with PPOM, * represent significant test result, SE is Standard deviation, *Exp_care_teaching* is the interaction between *Experience_teaching* and *Experience_care*, the responses is modeled as $\log \frac{P(Y_i \geq k)}{P(Y_i < k)}$

3.3.2 Opinion and Concern

We fitted 17 different proportional odds model with and without taking the covariate in to account for all teacher responses that related to opinion and concerns for gifted children. After checking the assumption for proportional odds, we found in 4 models assumption was not fulfill (test result in Appendix Table 18). We refitted the partial PPOM for those the assumption doesn't hold and we excluded the interaction between *Experience_teaching* and *Experience_care*, since it was not significant for all 17 models. In Table 11 below presents summary of test results that in order to determine whether opinion and concerns of the teachers different in three functions. We found a significant difference among functions for responses: $Overburdened$, $Outside\_of\_school$, $Collegues\_not\_open$, $Resources\_weaker\_children$, $Not\_feasible\_differentiation$, $Extra\_time\_differentiation$, $Less\_time\_differentiation$ and $Selfesteem\_pullout$ for both with and without taking the demographic characteristics of the teachers in to account since all their p_values are < 0.05 (implies rejected the null hypothesis that states $\beta_{12} = \beta_{13}$=0).

Table 19 in Appendix, contains the estimates of OR and the corresponding 95 % confidence interval (CI) for all parameters that responses related to opinion and concerns. We can conclude significant effect of parameters if 95% CI doesn't contains 1.

All responses related to opinion and concern, the probabilities modeled are summed over the responses having the lower ordered values in the response i.e. in the direction of **Strongly disagree to strongly agree**. After observing the overall significant difference among functions (previous paragraph), using pair wise test we found that there is a significant different between $function1$ with $function3$ and $function2$ with $function3$ in *overburdened* since OR of function was 0.371 and 0.440 respectively (both 95%CI doesn't contain 1). The cumulative odds of a teachers being respond disagree(strongly and slightly) relative to other responses category for pre-school teacher is 0.371 times remedial teacher in the opinion of gifted children becoming overburdened because of the educational adaptation by keeping the covariate *Experience_teaching* and *Experience_care* constant. Similarly the odds being in disagree versus the other response category for primary school teacher is 0.440 times remedial teacher in the opinion of gifted children becoming overburdened. These indicates that the probability of having negative (disagree) opinion on the children becoming overburdened is lower for pre-school and primary school teachers than remedial teachers. Regarding $Out\_side\_of school response$, only a significant difference between $function1$ and $function2$ was found (OR= 1.7386), the probability of having negative opinion (slightly and strongly disagree) about it is sufficient that children are challenged outside of school is higher for pre-school teacher than in primary school teachers given that the other covariate held constant. Concerning response about *colleagues_not_open*, we found difference between $function1$ with $function3$ and $function2$ with $function3$, hence pre-school and primary school teachers are more likely to disagree than remedial teacher(OR 5.179 and 3.231 respectively) about "I am afraid not all of my colleagues will be open to apply educational adaptations for gifted children". For response *Resources_weaker_children*, a significant difference observed between $function1$ and $function2$ with $function3$ (OR 0.342 and 0.423 respectively), the odds disagree versus the other response label for both pre-school and primary school teachers are lower than remedial teachers on believing that the limited financial resources should be dedicated to helping the weaker children in the classroom. For responses $Not\_feasible\_differentiation$, $Extra\_time\_differentiation$ and $Selfesteem\_pullout$ there is a difference between $function2$ verses $function3$ (OR was 0.482, 0.807, 0.485 respectively), which indicating that teachers in primary school have less negative(disagree) opinion than remedial teachers on individual differentiation for gifted children is not feasible , Curriculum compacting demands a lot of extra time which they do not have and Pull-out programs will have a negative effect on the self-esteem of the weaker children in the class. For

$Less\_time\_differentiation$, teaches both in pre-school and primary school have less negative (disagree) opinion than remedial teachers(OR 0.316 and 0.352 respectively) on having less time for the weaker children in the class, because of the curriculum compacting for the gifted children.

Table 11: likelihood ratio test that to test the significance of function with other and without (only function) covariate for opinion and concern responses

	With covariate			Without covariate		
Response	df	χ^2	p_value	df	χ^2	p_value
Convinced_benefit	2	2.9196	0.2323	2	2.9100	0.2335
Difficult_to_detect	2	2 1.817	0.4034	2	1.6200	0.4456
Not_confident	2	1.3868	0.4999	2	2.3500	0.3087
Overburdened	2	8.7240	0.0127 *	2	8.5100	0.0142*
Fear_of_failure	2	5.0412	0.0804	2	5.3800	0.0678
Being_a_child	2	2.7171	0.2570	2	4.2000	0.1224
Outside_of_school	2	10.240	0.0060 *	2	10.210	0.0061*
Parents_pressure	2	2.2279	0.3283	2	2.7700	0.2502
Collegues_not_open	2	29.916	$< .0001$*	2	28.270	$< .0001*$
Resources_weaker_children	2	11.901	0.0026 *	2	11.650	0.0029*
Long_term_effect	2	3.7164	0.1560	2	3.9800	0.1367
Vain	2	0.4800	0.7860	2	0.8900	0.6397
Not_feasible_differentiation	2	12.662	0.0018 *	2	11.710	0.0029*
Extra_time_differentiation	2	25.394	$< .0001$*	2	25.120	$< .0001$*
Less_time_differentiation	2	14.980	0.0006 *	2	12.910	0.0016*
Ache_for_differentiation	2	0.9139	0.6332	2	0.4400	0.8031
Selfesteem_pullout	2	7.0234	0.0298 *	2	5.6000	0.0608

where:df is degree of freedom and * represent significant test result for β_{11}=β_{12}=0

3.3.3 Specific knowledge for differentiation

For teachers responses related to specific knowledge for differentiation to gifted children, we fitted 17 different proportional odds model. All responses, the probabilities modeled are summed over the responses having the higher ordered values in the response i.e. in the direction of **Strongly agree to strongly disagree**. After testing the proportional odds assumptions result in Appendix Table 20, we refitted 7 models with partial proportional odds model in order to relax the covariate that required different slopes. The interaction between $Experience\_teaching$ and $Experience\_care$ was not significant for all responses,so that we excluded from the model. Table 12 below, contains test results for these responses to test whether a difference between functions with and without adjustment of the covariates. From the tests, we observed a statistical significant difference between primary and remedial teachers on the response for $Nice\_to\_have\_diff\_primaryschool$, $Same\_assignments\_diff\_primarysch$, $Choose\_diff\_primaryschool$ and $Mandatory\_diff\_primaryschool$ for both with and without the covariate since all p_values are less than 0.05(indicating that we rejected the null hypothesis that states $\beta_{12} = 0$). We also observed a significant difference between primary school and remedial teachers only without taking the covariate for responses On the other hand, for responses $Eliminate\_diff\_preschool$, $Challenging\_diff\_preschool$ and $Mandatory\_diff\_preschool$ we got a significant difference between pre-school and remedial teachers for both with and without taking the demographic characteristics of the teachers(rejected the null hypothesis that states $\beta_{11} = 0$) and for responses Nice_to_have_diff_preschool, and Choose_diff_preschool found a significant difference between pre-school and remedial teachers only for without taking the demographic characteristics of the teachers.

Looking at the results of the parameters estimates of OR and their corresponding 95 % CI given in Appendix Table 21, for those responses observed difference between functions. Regarding responses $Nice\_to\_have\_diff\_primaryschool$ and $Same\_assignments\_diff\_primarysch$, OR for functions was 3.752 and 34.250 respectively (both greater than 1) and 95%CI confidence interval for both OR doesn't contain 1. Implying that teachers in primary school the odds of being agree versus the other response category is 3.752 times remedial teachers on considering challenging exercises as 'nice to have' but not 'mandatory' for the gifted child and also 34.250 times remedial teachers on gifted children required to complete the same assignments as the other children in the class given the other covariates constant. Although, teachers in primary school are less likely agree than remedial teachers on they would let a gifted child choose its own challenging assignments and mandate the gifted child to work on the enrichment activities, since the OR of function was 0.302 and 0.315 for responses $Choose\_diff\_primaryschool$ and $Mandatory\_diff\_primaryschool$ respectively by keeping all other covariates constant. On the other hand, the probability of agree versus the other response category is less for pre-school teachers than remedial teachers on eliminating the already mastered curriculum of the gifted child and would replacing it with challenging exercises and mandate the gifted child to work on the enrichment activities (OR of function was 0.170 and 0.330 for $Eliminate\_diff\_preschool$ and $Mandatory\_diff\_preschool$ respectively). The probability of agree versus the other is higher for pre-school teachers than remedial teachers on offering challenging exercises when the gifted child is ready with its basis assignments since OR of function was 5.468 for response $Challenging\_diff\_preschool$. On continuing to offer challenging activities even if the working attitude of the gifted child regresses, teachers in pre-school have less attitude than remedial teachers (OR of function was 0.506 for response $Working\_attitude\_diff\_continu$).

Table 12: likelihood ratio test to test the significance of function with other and without (only function) covariate for specific knowledge (differentiation) responses

		With covariate			Without covariate		
Function	Response	df	χ^2	p_value	df	χ^2	p_value
Primary and remedial	Extra_basic_diff_primaryschool	1	0.3904	0.5301	1	0.26	0.6074
	Nice_to_have_diff_primaryschool	1	7.6258	0.0058*	1	15.7	$< .0001*$
	Same_assignments_diff_primarysch	1	11.2253	0.0008*	1	33.31	$< .0001*$
	Choose_diff_primaryschool	1	5.4413	0.0197*	1	9.9	0.0017 *
	Eliminate_diff_primaryschool	1	10.6692	0.0011*	1	18	$< .0001*$
	Challenging_diff_primaryschool	1	0.1903	0.6627	1	6.09	0.0136*
	Mandatory_diff_primaryschool	1	10.6750	0.0011 *	1	17.41	$< .0001*$
Pre and remedial	Extra_basic_diff_preschool	1	0.4678	0.4490	1	0.15	0.6963
	Nice_to_have_diff_preschool	1	0.0009	0.9766	1	13.24	0.0003*
	Same_assignments_diff_preschool	1	0.0983	0.7539	1	0.1	0.7461
	Choose_diff_preschool	1	0.7746	0.3788	1	7.42	0.0065 *
	Eliminate_diff_preschool	1	17.7393	$< .0001*$	1	20.45	$< .0001*$
	Challenging_diff_preschool	1	10.9599	0.0009*	1	9.56	0.002*
	Mandatory_diff_preschool	1	7.518	0.0061*	1	9.6	0.0019 *
pre, primary and remedial	Not_want_diff_continu	2	5.6084	0.0606	2	6.27	0.0435 *
	Many_mistakes_diff_continue	2	0.1380	0.9333	2	0.01	0.993
	Working_attitude_diff_continu	2	6.3966	0.0408*	2	5.5598	0.0620

Where * represent significant test result

3.3.4 Specific knowledge for acceleration

There were 4 different responses related to specific knowledge for accelerating gifted children, three of them were modeled using partial proportional odds model since the assumption of common slopes was not fulfilled (Table 22 in Appendix). From Table 13 below which contains test results among function, we can see that there is a significant difference among functions for responses *Acceleration* and *Opinion_child_accell* for both with and without covariate adjustments. But for the responses *Catch_up_accell* and *Gap_accell* only significant different observed after adjusting the covariate.

Under results in Table 23 in Appendix that contains the estimates of OR and the corresponding 95% confidence interval (CI) for all parameters for responses specific knowledge on Acceleration. All responses, the probabilities modeled are summed over the responses having the higher ordered values in the response i.e. in the direction of **agree to disagree**. It was found that only a significant difference between $function1$ versus $function3$ and $function2$ versus $function3$ since the p_value was 0.0026 and 0.0034(also the 95% CI for OR doesn't contain

1) respectively for teachers response on in favor of accelerated gifted children. Teachers in pre-school the odds of agree verses disagree or neutral in favor of accelerating gifted children is 0.204 the remedial teacher and the odds of being agree versus disagree and neutral in favor of accelerating gifted children for primary school teacher is 0.259 times remedial teacher given other covariates held constant. *This indicates that remedial teachers more agree in favor of accelerating gifted children than pre-school teachers and primary school teachers.* Similarly a significant difference observed between all pair wise functions on *Opinion_child_accell*, hence the probability of having positive opinion(agree) verses the other response level in always take into account the opinion of the gifted child that qualifies for an acceleration for pre-school teachers and primary teachers is lower than remedial teachers since the OR was 0.264 and 0.510 respectively. Also all pair wise significant difference between functions observed for responses *Catch_up_accell*, the odds of agree versus the other is higher for pre-school and primary school teacher than remedial teacher on (OR 24.622 and 3.3029 respectively). These implies that pre-school and primary school teachers agree more than the remedial teachers in the importance for a gifted child to catch up on the missed subjects of the skipped grade before the next school year starts. Regarding response *Gap_accell* responses a significant different observed between $function2$ and $function3$ (p_value =0.0126), and the probability of having positive response (agree) versus the other response level for primary school teachers is higher than remedial teachers on "i would question the acceleration when the gifted child shows a 'gap' in its knowledge at the beginning of the new school year" since OR was 2.55. Concerning covariates *Experience_teaching* and *Experience_care*, only significant effect of teaching experience for *Acceleration*, *Opinion_child_accell*, and *Catch_up_accell* was observed and significant effect of care experience for *Catch_up_accell* and *Gap_accell* was observed.

Table 13: likelihood ratio test to test the significance of function other and without (only function) covariate for specific knowledge(Acceleration) responses

Response	With covariate df	χ^2	p_value	Without covariate df	χ^2	p_value
Accelleration	2	9.125	0.0100 *	2	10.1546	0.0062 *
Opinion_child_accell	2	14.9090	0.0006*	2	20.0923	$< .0001*$
Catch_up_accell	2	88.2197	$< .0001*$	2	1.3397	0.5118
Gap_accell	1	6.2176	0.0126*	1	3.2896	0.0697

Where *represents significant test result for β_{11}=$\beta_{12} = 0$

3.3.5 Comparison of Primary school teachers between classes

We fitted different POM for these particular questions and the model is formulated as follows.

$$\log \frac{P(Y_i \leq k)}{P(Y_i > k)} = \alpha_k + \beta_{1j} * classes_i + \beta_2 * Experience\_teaching_i + \beta_3 * classes_i * Experience\_teaching_i$$

Where: Y_i is the response of the ith primary school teachter for i=1,2,...,61. β_{1j} measure the log odds effect of classes on the responses and β_3 is the effect of the interaction between classes and teaching experience. The other parameters have the same interpretation as POM (in section 2.2)

In order to determine whether there is a difference primary school teachers between cleasses, such as difference between teachers in first lower class, second lower class, third lower class with fourth lower class, fifth lower class, sixth lower class (class 1,2,3 versus class 4,5,6) and difference between teachers in first lower class, third lower class, fifth lower class, with second lower class, with fourth lower class, sixth lower class (class 1,3,5 versus class 2,4,6) we applied Likelihood ratio test based on contrast.

Under Table 14 below, we can see that there is no statistically significant difference between classes (class 1,2,3 versus class 4,5,6) and (class 1,3,5 versus class 2,4,6) on teachers having knowledge in educational adaptation for gifted children since the p_value was 0.4128 and 0.4502 respectively. The same conclusion was done for teachers having experience in applying educational adaptation hence the hypothesis that there is no statistical difference between classes (H_0:class 1,2,3 = class 4,5,6 and H_0: class 1,3,5 = class 2,4,6) was not rejected since the p_value 0.6325 and 0.7342 respectively. These test results supported insight obtained from exploratory data analysis.
Results presented in Table 15 below, observed only a significant test result to the difference between classes of class 1, 3, 5 versus class 2, 4, 6 response $Same\_assignments\_diff\_primaryschool$ since the p_value was 0.0398. Test result for the remaining responses given in Appendix Table 24, there were no statistical difference was observed between classes in primary school teachers.

Table 14: Contrast test results between primary school classes on Knowledge and Experience for educational adaptation

	Knowledge		Experience	
Contrast	χ^2(df)	P_value	χ^2(df)	P_value
class 1,2,3 = class 4,5,6	0.6708(1)	0.4128	0.2287(1)	0.6325
class 1,3,5 = class 2,4,6	0.5702(1)	0.4502	0.1153(1)	0.7342

Table 15: Contrast test results between primary school classes for selcted rsponses

Contrast	Convinced_benefit		Difficult_to_detect		Same_assignments_diff_ primaryschool		Choose_diff_ primaryschool	
	χ^2(df)	p_value	χ^2(df)	p_value	χ^2(df)	p_value	χ^2(df)	p_value
class 1,2,3 = class 4,5,6	0.4054(1)	0.5243 1	2.2006(1)	0.1380	1.4071(1)	0.2355	3.6950(1)	0.0546
class 1,3,5 = class 2,4,6	0.3790(1)	0.5381	0.4478(1)	0.5034	4.2244(1)	0.0398*	3.6950(1)	0.0546

where: * represents a significant test result and df is degree of freedom

4 Discussions and conclusions

In this study, we have analyzed the survey data collected on Belgian school teachers focusing on gifted children in order to accommodate the more advanced, gifted learners in the classroom developed in-depth training program for school personnel and parents. The aim of the thesis was to look at the baseline characteristics (pre-training) of teachers in pre-school, primary school and remedial teachers on their knowledge, experience, opinion, and specific knowledge about differentiation and acceleration about gifted children.

To answer any study objective, understanding the nature of the data was the crucial step. In this case the level of outcome of the variable of interest had ordinal nature. Therefore, model which takes into account this ordinality were fitted using Log-linear model (Linear by linear association), proportional odds model (POM), and partial proportional odds model (PPOM) in order to address the research questions. We fitted PPOM for the case of the proportional odds assumption in POM is violated. Likelihood ratio test (LRT) was used in order to test the difference between types of teachers (pre-school, primary school and remedial teachers) in their knowledge, experience and opinion on gifted children. Deviance and Pearson statistics were used to test the goodness-of-fit of the fitted models and score test and empirical cumulative logit plots were applied in order to determine the proportional odds assumption.

The main finding for the case of outcome related to educational adaptation, we found a positive association between Knowledge and Experience, hence the higher having knowledge the higher having experience for educational adaptation. We also found difference among function (pre-school, primary school and remedial teachers), in having knowledge to a large extent is higher for remedial teachers and primary school teachers and it is lower for pre-school teachers. But no difference among function was observed in having Experience for educational adaptation. The effect of experience as a care teacher is depends on teaching experience on having Knowledge and Experience for educational adaptation.

Concerning teachers' opinion on gifted children, we found some different attitudes among them. Such as, teachers in in pre-school and primary scholl have lower negative attitude (disagree) than remedial teacher in gifted children become overburdened because of educational adaptation. Primary school teachers have positive opinion than Pre-school teachers on sufficient that children are challenged outside of school given that teaching experience held fixed. Both pre-school and primary school teachers have less disagree than remedial teachers on believing that the limited financial resources should be dedicated to helping the weaker children in the classroom. Only in four outcomes (Convinced_benefit, Parents_pressure, Long_term_effect and Not_feasible_differentiation), teaching experience have a significant effect on teachers' opinion and concern about gifted children. Also having experience on caring students has some effects on teachers attitude on gifted children.

There is some difference between pre-school and remedial teachers and between primary school and remedial teaches on having specific knowledge for differentiation and acceleration. Teachers in primary school are more agree than remedial teachers on considering challenging exercises as nice to have but not mandatory for gifted child. Pre-school teachers are less likely than remedial teachers on eliminating the already mastered curriculum of gifted child and would replace with challenging exercises. Pre-school and primary school teachers have negative response (disagree) compared to remedial teachers on in favoring of accelerating gifted children. This finding is also consistent with some literature (Lassig et al, 2009). Although, pre-school teachers and primary school teachers believe on the important of a gifted child can catch up the missed subjects of the skipped grade before the next school year starts than remedial teachers. Teaching experience has significant effects on teachers specific knowledge about acceleration.

In summary, improving teachers competencies, skills and behavior requires improving teachers attitudes towards gifted children and their education. Education and training reforms for gifted and talented helps schools to create a school culture that priorities gifted education, enhance teachers attitudes, skills and ability that recognizes and meets the needs of gifted children. In this regard, adopting and refining best practice in gifted education that enables gifted children to develop their full potential can benefit society as well as the individual.

Recommedations: In this analysis, we assumed teachers' responses are not correlated, however in reality teachers from the same school may have similar knowledge and attitude towards gifted children. Although, based on the interest of the owners of the study we analyzed each of the response of the teachers separately. However, the multivariate version of the analysis may give be appropriate since it takes into account the correlated nature of the responses from teachers from the same school. The number of teachers examined differed across the three groups (pre-school, primary school and remedial teachers) hence, to make the groups more comparable, the sizes should be made equal.

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Appendix

Table 16: Response variables and their description

Response type of variable	Variable name	Variable discription
Knowledge (EA)	Knowledge	To what extend do you have knowledge about the ecucational adaptations for gifted children?
Experience (EA)	Experience	To what extend are you experienced in applying educational adaptations for gifted children.
Opinion and concerns	Convinced_benefit	I am convinced that educational adaptations are beneficial for gifted children.
Opinion and concerns	Difficult_to_detect	It is hard to detect which children need more challenge at school.
Opinion and concerns	Not_confident	I do not feel confident enough to apply educational adaptations for gifted children.
Opinion and concerns	Overburdened	Gifted children will become overburdened because of the educational adaptations.
Opinion and concerns	Fear_of_failure	Gifted children will suffer from 'fear of failure' because of the educational adaptations.
Opinion and concerns	Being_a_child	Too much attention is payed to the achievements of the child and not to 'just being a child'.
Opinion and concerns	Outside_of_school	It is sufficient that children are challenged outside of school.
Opinion and concerns	Parents_pressure	I am worried that the parents of gifted children will put me under pressure.
Opinion and concerns	Collegues_not_open	I am afraid that not all of my collegues will be open to applying educational adaptations for gifted children.
Opinion and concerns	Resources_weaker_children	I believe that the limited financial resources should be dedicated to helping the weaker children in the classroom.
Opinion and concerns	Long_term_effect	Special educational arrangements will have a negative long-term effect on the well-being of gifted children.
Opinion and concerns	Vain	Gifted children will become vain because of the educational adaptations.
Opinion and concerns	Not_feasible_differentiation	Individual differentation for gifted children is not feasible.
Opinion and concerns	Extra_time_differentiation	Curriculum compacting demands a lot of extra time which I do not have.
Opinion and concerns	Less_time_differentiation	I will have less time for the weaker children in the class, because ot the curriculum compacting for the gifted children.
Opinion and concerns	Ache_for_differentiation	The weaker children in the class will also ache for these special educational arrangements.
Opinion and concerns	Selfesteem_pullout	Pull-out programs will have a negative effect on the self-esteem of the weaker children in the class.
Specific knowledge (Diff)	Extra_basic_diff_primaryschool	I would offer more of the same (basic) excercises, when the gifted child is ready with its basis assignments.
Specific knowledge (Diff)	Nice_to_have_diff_primaryschool	I consider challenging excercises as 'nice to have' but not 'mandatory' for the gifted child.
Specific knowledge (Diff)	Same_assignments_diff_primary	Gifted children are required to complete the same assignments as the other children in the class.
Specific knowledge (Diff)	Choose_diff_primaryschool	I would let a gifted child choose its own challenging assignments.
Specific knowledge (Diff)	Eliminate_diff_primaryschool	I would eliminate the already mastered curriculum of the gifted child and would replace it with challenging excercises.
Specific knowledge (Diff)	Challenging_diff_primaryschool	I would offer challenging excercises, when the gifted child is ready with its basis assignments.
Specific knowledge (Diff)	Mandatory_diff_primaryschool	I would mandate the gifted child to work on the enrichment activities.
Specific knowledge (Diff)	Extra_basic_diff_preschool	I would offer more of the same (basic) excercises, when the gifted child is ready with its basis assignments.
Specific knowledge (Diff)	Nice_to_have_diff_preschool	I consider challenging excercises as 'nice to have' but not 'mandatory' for the gifted child.
Specific knowledge (Diff)	Same_assignments_diff_preschool	Gifted children are required to complete the same assignments as the other children in the class.
Specific knowledge (Diff)	Choose_diff_preschool	I would let a gifted child choose its own challenging assignments.
Specific knowledge (Diff)	Eliminate_diff_preschool	I would eliminate the already mastered curriculum of the gifted child and would replace it with challenging excercises.
Specific knowledge (Diff)	Challenging_diff_preschool	I would offer challenging excercises, when the gifted child is ready with its basis assignments.
Specific knowledge (Diff)	Mandatory_diff_preschool	I would mandate the gifted child to work on the enrichment activities.
Specific knowledge (Diff)	Not_want_diff_continu	I would continue to offer challenging excercises, even if the child doesn't want to make them or gets frustrated.
Specific knowledge (Diff)	Many_mistakes_diff_continue	I would continue to offer challenging excercises, even if the child makes a lot of mistakes.
Specific knowledge (Diff)	Working_attitude_diff_continu	I would continue to offer challenging activities, even if the working attitude of the gifted child regresses.
Opinion and concerns	Accelleration	I am in favour of accelerating gifted children (i.c. grade skipping).
Specific knowledge (Acce)	Opinion_child_accell	I always take into account the opinion of the gifted child that qualifies for an accelaration.
Specific knowledge (Acce)	Catch_up_accell	It is important that a gifted child can catch up the missed subjects of the skipped grade before the next school year starts.
Specific knowledge (Acce)	Gap_accell	I would question the accelaration when the gifted child shows a 'gap' in its knowledge at the beginning of the new school year.

Where: EA is Educational adaptation, Diff is Diffrentaitaion, Acce is Acceleration

Figure 6: Bar chart some selected responses for opinion and conserns verseses function

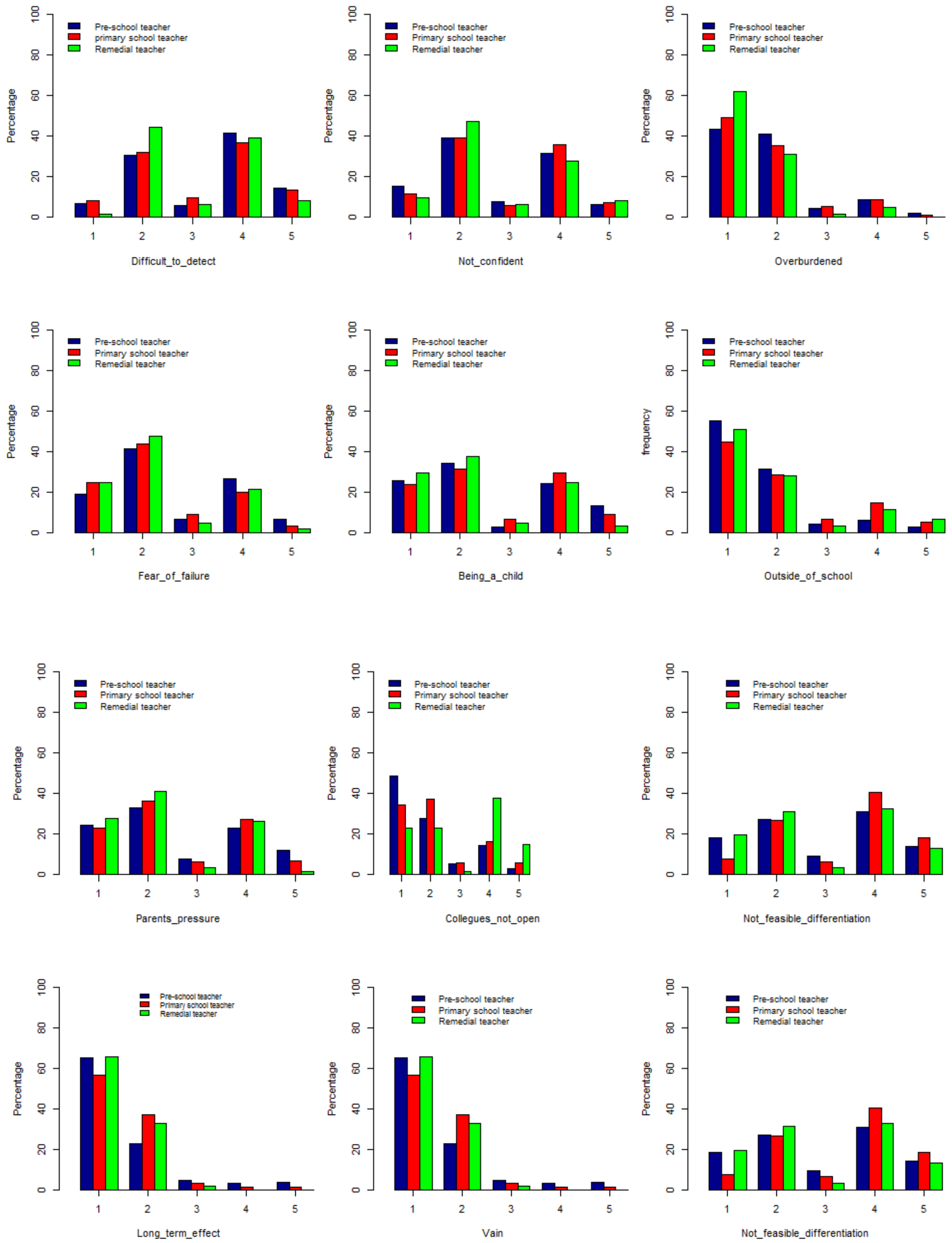

Figure 7: Bar chart of some selected responses of primary school and remedial teachers for specific knowledge for differentioan verses function

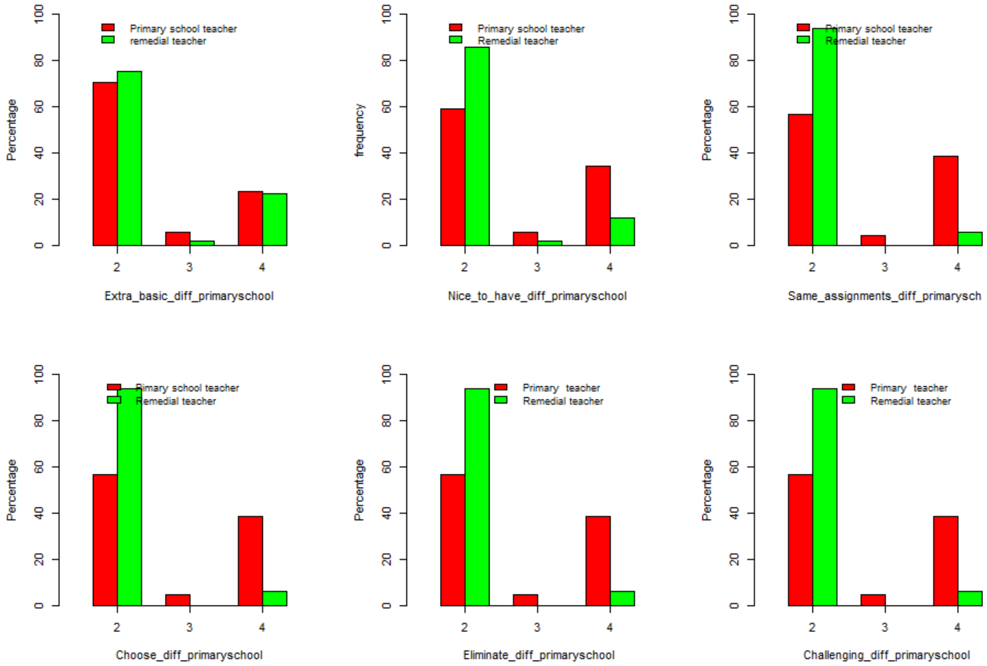

Figure 8: Bar chart of some selected responses of pre-school and remedial teachers for specific knowledge for differentioan verses function

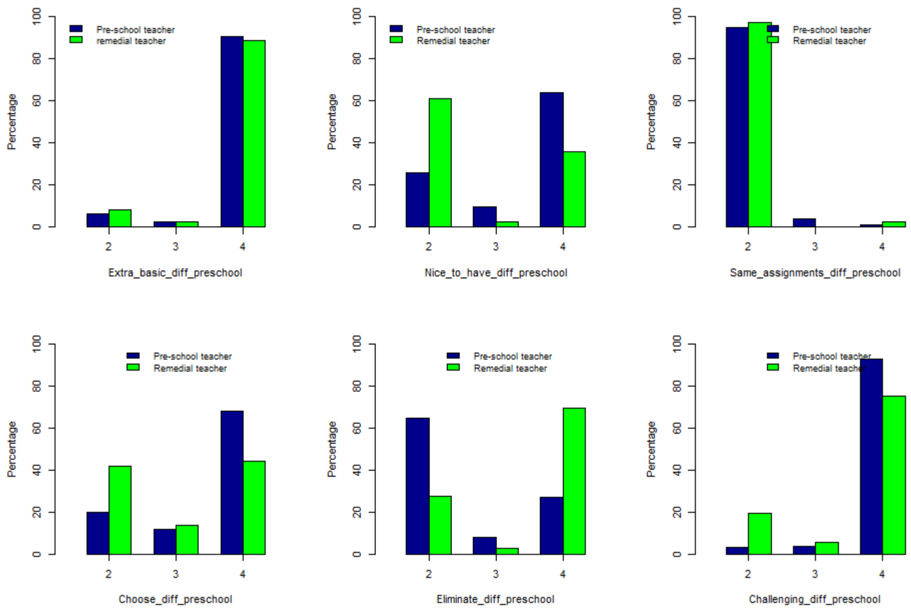

Figure 9: Bar charst of responses for specific knowledge on Acceleration vs function

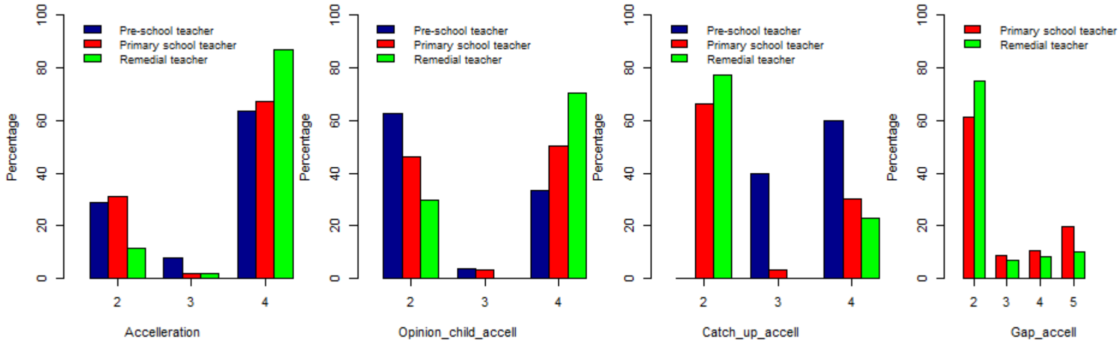

Table 17: likelihood ratio test to test the significance of function with other and without (only function) covariate for knowledge and Experience for educational adaptation

	With covariate		Without covariate	
Response	χ^2(df)	p_value	χ^2(df)	p_value
Kowledge	32.9862(2)	$< .0001*$	30.7596(2)	$< .0001*$
Experience	2.5747(2)	0.2760	2.6236(2)	0.2693

Where *represents significant test result for $\beta_1=\beta_2=\beta_3$

Table 18: Score tests for equal slopes assumption for responses related opinion and concerns

Test result	3	4	5	6	7	8	9	10	11	12	13	14	17	16	17	18	19
Chi-Square	15.7184	9.3942	9.5281	69.2028	6.6327	13.8923	17.3187	68.5928	18.2599	5.3441	20.5361	17.1074	71.1884	8.3427	20.4023	27.8143	15.0845
DF	4	12	12	12	12	12	12	12	12	12	12	12	12	12	12	12	15
P_value	0.0034*	0.6689	0.6573	0.0001*	0.8809	0.3076	0.1380	0.0001*	0.1080	0.9455	0.0576	0.1456	0.0001*	0.7578	0.0598	0.0528	0.2368

Where 3=Convinced_benefit, 4=Difficult_to_detect,...,19=Selfesteem_pullout and * represents significant test result.

		with covariate		Without covariate	
Response	Parameters	OR	95%CI	OR	95%CI
$Convinced\_benefit^a$	Function 1vs3	4.375	(0.533 ,35.937)	1.564	(0.437 ,5.598)
	Function 2vs 3	5.610	(0.704, 44.723)	2.017	(0.593, 6.862)
	Experience_teaching 2	1.037*	(1.004, 1.071)		
	Experience_teaching 3	1.011*	(1.001 ,1.025)		
	Experience_care	1.024	(0.996, 1.053)		
Difficult_to_detect	Function 1vs 3	0.696	(0.388, 1.251)	0.751	(0.443, 1.274)
	Function 2vs 3	0.827	(0.469, 1.458)	0.893	(0.537 ,1.485)
	Experience_teaching	0.995	(0.986 ,1.004)		

	Experience_care	0.997	(0.983 ,1.011)		
Not_confident	Function 1vs 3	1.141	(0.634, 2.054)	1.047	(0.616, 1.780)
	Function 2vs3	0.927	(0.525, 1.638)	0.852	(0.511, 1.419)
	Experience_teaching	0.998	(0.990, 1.007)		
	Experience_care	1.005	(0.991, 1.019)		
Overburdened[a]	Function 1vs 3	0.371*	(0.192, 0.716)	0.463	(0.259, 0.826)
	Function 2vs 3	0.440*	(0.232, 0.838)	0.551	(0.315, 0.965)
	Experience_teaching 1	0.998	(0.989 ,1.008)		
	Experience_teaching 2	0.990	(0.979 ,1.002)		
	Experience_teaching 3	0.998	(0.984, 1.013)		
	Experience_teaching 4	0.981	(0.958, 1.005)		
	Experience_care	0.991	(0.977, 1.004)		
Fear_of_failure	Function 1vs3	0.592	(0.328 ,1.069)	0.623	(0.365 ,1.061)
	Function 1vs 3	0.879	(0.496, 1.557)	0.923	(0.553, 1.541)
	Experience_teaching	1.003	(0.995, 1.012)		
	Experience_care	0.997	(0.984, 1.011)		
Being_a_child	Function 1vs3	0.651	(0.364 ,1.164)	0.692	(0.409 , 1.168)
	Function 2vs3	0.624	(0.355, 1.097)	0.660	(0.398 , 1.093)
	Experience_teaching	0.624	(0.355, 1.097)		
	Experience_care	0.624	(0.355, 1.097)		
Outside_of_school	Function 1vs3	1.013	(0.545, 1.881)	1.356	(0.783, 2.347)
	Function 2vs3	0.583	(0.32,1 1.057)	0.785	(0.466 ,1.322)
	Experience_teaching	0.997	(0.988 ,1.005)		
	Experience_care	0.986*	(0.972, 0.999)		
Parents_pressure[a]	Function 1vs 3	0.643	(0.359, 1.152)	4.347*	(2.543, 7.431)
	Function 2vs3	0.687	(0.391, 1.206)	4.347*	(2.543, 7.431)
	Experience_teaching 1	1.007	(0.996, 1.017)		
	Experience_teaching 2	1.015*	(1.004, 1.025)		
	Experience_teaching 3	1.021*	(1.009 ,1.033)		
	Experience_teaching 4	1.043*	(1.011, 1.076)		
	Experience_care1	0.996	(0.983, 1.009)		
Collegues_not_open	Function 1vs 3	5.179*	(2.859 ,9.381)	4.347*	(2.543, 7.431)
	Function 2vs3	3.231*	(1.831, 5.699)	2.722*	(1.638 ,4.522)
	Experience_teaching	0.995	(0.986 , 1.003)		
	Experience_care	1.009	(0.995, 1.023)		
Resources_weaker_children	Function 1vs 3	0.342*	(0.186, 0.630)	0.392*	(0.225 , 0.681)
	Function 2vs 3	0.423*	(0.234, 0.764)	0.520*	(0.309, 0.876)
	Experience_teaching	0.423*	(0.234 ,0.764)		
	Experience_care	0.423*	(0.234 , 0.764)		
Long_term_effect	Function 1vs 3	0.691*	(0.347 ,1.379)	0.840	(0.459, 1.537)
	Function 2vs 3	0.550	(0.282 ,1.073)	0.673	(0.377 ,1.202)
	Experience_teaching	0.991	(0.982, 1.000)		
	Experience_care	0.992	(0.977 ,1.006)		
Vain	Function 1vs3	0.823	(0.450 ,1.506)	0.781	(0.453, 1.349)

	Function 2vs3	1.246	(0.694, 2.239)	0.759	(0.449, 1.284)
	Experience_teaching	0.802	(0.447, 1.441)		
	Experience_care	1.002	(0.993, 1.011)		
Not_feasible_differentiation[a]	Function 1vs3	0.828	(0.456, 1.503)	0.913	(0.542 ,1.536)
	Function 2vs 3	0.482*	(0.270 ,0.860)	0.532	(0.322 ,0.882)
	Experience_teaching	0.998	(0.989 ,1.006)		
	Experience_care 1	0.994	(0.972, 1.016)		
	Experience_care 2	0.993	(0.978, 1.008)		
	Experience_care 3	0.997	(0.983 , 1.012)		
	Experience_care 4	0.998	(0.977 ,1.019)		
Extra_time_differentiation	Function 1vs 3	0.993	(0.555, 1.775)	0.992	(0.978, 1.006)
	Function 2vs 3	0.897*	(0.808, 0.997)	0.511	(0.307 ,0.851)
	Experience_teaching	0.992	(0.978 ,1.006)		
	Experience_care	0.992	(0.978, 1.006)		
Less_time_differentiation	Function 1vs 3	0.316*	(0.174, 0.572)	0.420*	(0.247 ,0.715)
	Function 2vs 3	0.352*	(0.198, 0.627)	0.465*	(0.279, 0.775)
	Experience_teaching	1.005	(0.996, 1.013)		
	Experience_care	0.986	(0.973, 1.000)		
Ache_for_differentiation	Function 1vs 3	0.813	(0.454 ,1.455)	0.942	(0.558, 1.591)
	Function 2vs 3	0.762	(0.433, 1.339)	0.884	(0.534 ,1.464)
	Experience_teaching	1.004	(0.995 ,1.012)		
	Experience_care	0.992	(0.978, 1.005)		
Selfesteem_pullout	Function 1vs 3	0.636	(0.352 ,1.149)	0.756	(0.441 , 1.297)
	Function 2vs 3	0.485*	(0.273, 0.862)	0.57*	(0.339 , 0.96)
	Experience_teaching	1.005	(0.996 ,1.014)		
	Experience_care	0.988	(0.975 ,1.002)		

Table 19: Maximum likelihood odds ratios estimates and the corresponding confidence interval for responses related to opinion and concern. Where *response*[a] Represents the response is modeled using PPOM and * represent the estimate is significant since 95%CI doesn't contain 1 and the responses are modeled $\log \frac{P(Y_i \leq k)}{P(Y_i > k)}$

Table 20: Score tests for equal slopes assumption for responses related to specific knowledge for differentation

Test result	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36
Chi-Square	12.7473	8.3623	64.9423	6.9386	7.6262	4.2956	20.6725	2.0397	21.7261	9.2956	2.0268	6.8172	2.4850	42.8345	3.3227	12.9100	24.1417
DF	3	3	3	3	3	3	3	3	3	3	3	3	3	3	8	8	8
P_value	0.0052*	0.0391*	<.0001*	0.0739	0.1062	0.36748	0.0001 *	0.7285	<.0001*	0.05412	0.5669	0.0779	0.4780	<.0001*	0.9125	0.1150	0.0022*

Where 20=Extra_basic_diff_primaryschool, 21=Nice_to_have_diff_primaryschool ,...,36=Working_attitude_diff_continue and * represents significant test result

Response	Parameters	with covariate OR	95%CI	OR	Without covariate 95%CI
Extra_basic_diff_primaryschool[a]	Function 2vs3	1.287	(0.583, 2.839)	0.833	(0.414 , 1.676)
	Experience_teaching 4	0.976*	(0.958, 0.995)		
	Experience_teaching 3	0.981*	(0.964, 0.998)		
	Experience_care	1.006	(0.986, 1.027)		
Nice_to_have_diff_primaryschool[a]	Function 2vs3	3.752*	(1.468, 9.590)	0.211*	(0.087 , 0.512)
	Experience_teaching 4	0.994*	(0.979, 0.999)		
	Experience_teaching 3	0.998*	(0.986 1.0000)		
	Experience_care 4	1.026	(0.990 1.065)		
	Experience_care 3	0.987	(0.954, 1.022)		
Same_assignments_diff_primary[a]	Function 2vs3	34.250*	(4.334, 70.655)	0.058*	(0.014 , 0.243)
	Experience_teaching 4	0.998	(0.985, 1.012)		
	Experience_teaching 3	1.005	(0.993, 1.018)		
	Experience_care	1.029*	(1.001, 1.058)		
Choose_diff_primaryschool	Function 2vs3	0.302*	(0.110, 0.826)	0.261*	(0.099 , 0.685)
	Experience_teaching	1.007	(0.993, 1.022)		
	Experience_care3	0.990	(0.969 ,1.011)		
Eliminate_diff_primaryschool	Function 2vs3	0.126*	(0.036, 0.437)	6.371*	(2.218 , 18.3)
	Experience_teaching	0.996	(0.985, 1.008)		
	Experience_care	0.984	(0.963 ,1.006)		
Challenging_diff_primaryschool	Function 2vs3	1.433	(0.285, 7.217)	3.662*	(1.105 , 12.137)
	Experience_teaching	0.992	(0.979, 1.006)		
	Experience_care	1.989	(0.780, 5.071)		
Mandatory_diff_primaryschool[a]	Function 2vs3	0.315*	(0.158, 0.630)	3.825*	(2.062 , 7.097)
	Experience_teaching 4	1.014*	(1.003, 1.068)		
	Experience_teaching 3	0.996	(0.982, 1.010)		
	Experience_care	1.003	(0.986, 1.021)		
Extra_basic_diff_preschool	Function 2vs3	1.672	(0.384, 7.286)	0.79	(0.248 , 2.517)
	Experience_teaching	0.999	(0.973, 1.027)		
	Experience_care	1.055	(0.845, 1.318)		
Nice_to_have_diff_preschool[a]	Function 2vs3	0.984	(0.324, 2.985)	0.263*	(0.128 , 0.538)
	Experience_teaching 4	0.993	(0.978, 1.009)		
	Experience_teaching 3	0.994	(0.999, 1.012)		
	Experience_care	0.716*	(0.553, 0.928)		
Same_assignments_diff_preschool	Function 2vs3	0.656	(0.047 ,9.136)	0.713	(0.086 , 5.89)
	Experience_teaching	1.025*	(1.001, 1.050)		
	Experience_care	0.785	(0.365, 1.690)		
Choose_diff_preschool	Function 2vs3	1.558	(0.580 ,4.185)	0.378*	(0.189 , 0.755)
	Experience_teaching	1.011	(0.992, 1.031)		
	Experience_care	0.909	(0.790 ,1.047)		
Eliminate_diff_preschool	Function 2vs3	0.170*	(0.075 ,0.388)	5.422*	(2.533 , 11.606)

	Experience_teaching	1.005	(0.989 ,1.022)		
	Experience_care	0.996	(0.966, 1.026)		
Challenging_diff_preschool	Function 2vs3	5.468	(2.000, 14.951)	0.206*	(0.080 , 0.531)
	Experience_teaching	0.988	(0.965, 1.012)		
	Experience_teaching	1.662	(0.602 , 4.584)		
	Experience_care	1.017	(0.966, 1.070)		
Mandatory_diff_preschool	Function 2vs3	0.330*	(0.149 ,0.729)	3.196*	(1.557 , 6.562)
	Experience_teaching 4	0.991	(0.971 ,1.013)		
	Experience_teaching 3	0.726*	(0.375 , 0.904)		
	Experience_care	1.008	(0.976 1.041)		
Not_want_diff_continue	Function 1vs3	0.485*	(0.259, 0.907)	2.032*	(1.145 , 3.608)
	Function 2vs3	0.633	(0.346, 1.160)	1.564	(0.901 , 2.715)
	Experience_teaching	0.996	(0.987, 1.005)		
	Experience_care	1.000	(0.986 ,1.015)		
Many_mistakes_diff_continue	Function 1vs3	0.901	(0.496, 1.635)	0.99	(0.574 , 1.708)
	Function 2vs3	0.898	(0.504, 1.602)	1.012	(0.598 , 1.711)
	Experience_teaching	1.004	(0.995 ,1.013)		
	Experience_care	0.992	(0.978, 1.006)		
$Working\_attitude\_diff\_continue^{a}$	Function 1vs3	0.506*	(0.273, 0.937)	1.829	(1.049 , 3.187)
	Function 2 vs 3	0.716	(0.393 ,1.306)	1.319	(0.772 , 2.251)
	Experience_teaching 4	0.999	(0.989 ,1.008)		
	Experience_teaching 3	0.928*	(0.919, 0.997)		
	Experience_teaching 2	0.969*	(0.912, 0.999)		
	Experience_care	0.993	(0.979 ,1.008)		

Table 21: Maximum likelihood odds ratios estimates and the corresponding confidence interval specific knowledge for differentiation. Where: $Response^{a}$ represents the response is modeled using PPOM and * represent the estimate is significant since 95%CI doesn't contain 1 and the responses are modeled as log $\frac{P(Y_i \geq k)}{P(Y_i < k)}$

Table 22: Score tests for equal slopes assumption for responses related to specific knowledge for Acceleration

Test result	37	38	39	40
Chi-Square	20.3309	63.6048 4	254.2856	5.2637
DF	4	4	4	9
P_value	0.0004*	<.0001*	<.0001*	0.8107

Where: 37=Acceleration,...,40=Gap_accell, and * represents significant test result

Table 23: Maximum likelihood odds ratios estimates and the corresponding confidence interval for specific knowledge(acceleration) responses

		with covariate		Without covariate	
Response	Parameters	OR	95%CI	OR	95%CI
Accelleration[a]	Function 1vs3	0.240*	(0.095, 0.607)	3.486*	(1.562 , 7.783)
	Function 2vs3	0.259*	(0.104 ,0.647)	3.313*	(1.508 7.277)
	Experience_teaching 4	1.005 (0.994	1.016)		
	Experience_teaching 3	1.006*	(1.005, 1.018)		
	Experience_care	0.992	(0.973 ,1.012)		
Opinion_child_accell[a]	Function 1vs3	0.264*	(0.125 ,0.557)	4*	(2.02 , 7.92)
	Function 2vs3	0.510	(0.248,1.047)	2.052*	(1.068 , 3.94)
	Experience_teaching 4	0.979*	(0.966 ,0.992)		
	Experience_teaching 3	0.980*	(0.967, 0.993)		
	Experience_care	1.017	(0.993,1.041)		
Catch_up_accell[a]	Function 1vs3	24.622	(9.479, 63.956)	0.064*	(0.031 , 0.132)
	Function 2vs3	3.029*	(1.181, 7.770)	0.485*	(0.241 , 0.977)
	Experience_teaching 4	1.001	(0.988, 1.015)		
	Experience_teaching 3	0.996*	(0.984 ,0.999)		
	Experience_care	1.028*	(1.006, 1.050)		
Gap_accell	Function 2vs3	2.555*	(1.222, 5.340)	0.592	(0.32 ,1.097)
	Experience_teaching	1.004*	(0.993, 1.015)		
	Experience_care	1.018*	(1.003 ,1.033)		

Where: $Response^a$ represents the response is PPOM and * represent the estimate is significant since 95%CI doesn't contain 1 and the responses are modeled as $\log \frac{P(Y_i \geq k)}{P(Y_i < k)}$.

Table 24: Contrast test results between primary school classes

Contrast	Not_confident		Overburdened		Fear_of_failure		Being_a_child	
	χ^2(df)	p_value	χ^2(df)	p_value	χ^2(df)	p_value	χ^2(df)	p_value
LS_class 1,2,3 = LS_class 4,5,6	0.1409(1)	0.7074	0.4541(1)	0.5004	0.0002(1)	0.9898	1.8231(1)	0.1769
LS_class 1,3,5 = LS_class 2,4,6	0.0076(1)	0.9304	0.2766(1)	0.5989	1.4880(1)	0.2225	1.9013(1)	0.1679
	Outside_of_school		Parents_pressure		Collegues_not_open		Resources_weaker _children	
	χ^2(df)	p_value	χ^2(df)	p_value	χ^2(df)	p_value	χ^2(df)	p_value
LS_class 1,2,3 = LS_class 4,5,6	1.4037(1)	0.2361	1.3791(1)	0.2403	1.5137(1)	0.2186	0.1300(1)	0.7185
LS_class 1,3,5 = LS_class 2,4,6	1.6412(1)	0.200	0.5517(1)	0.4576	0.0009(1)	0.9754	2.7589(1)	0.0967
	Long_term _ffect		Vain		Not_feasible _differentiation		Extra_time _differentiation	
	χ^2(df)	p_value	χ^2(df)	p_value	χ^2(df)	p_value	χ^2(df)	p_value
LS_class 1,2,3 = LS_class 4,5,6	0.2507(1)	0.6166	0.0009(1)	0.9761	0.9135(1)	0.3392	0.0258(1)	0.8725
LS_class 1,3,5 = LS_class 2,4,6	0.4923(1)	0.4829	0.0142(1)	0.9050	0.7384(1)	0.3902	1.5595(1)	0.2117
	Less_time _differentiation		Ache_for _differentiation		Selfesteem_pullout		Extra_basic_diff _primaryschool	
	χ^2(df)	p_value	χ^2(df)	p_value	χ^2(df)	p_value	χ^2(df)	p_value
LS_class 1,2,3 = LS_class 4,5,6	2.8211(1)	0.0930	0.3469(1)	0.5559	1.3515(1)	0.2450	0.0002(1)	0.9899
LS_class 1,3,5 = LS_class 2,4,6	1.3590(1)	0.2437	0.1081(1)	0.7423	0.0005(1)	0.9816	1.5303(1)	0.2161
	Nice_to_have_ diff_primaryschool		Eliminate_diff _primaryschool		Challenging_diff _primaryschool		Mandatory_diff _primaryschool	
	χ^2(df)	p_value	χ^2(df)	p_value	χ^2(df)	p_value	χ^2(df)	p_value
LS_class 1,2,3 = LS_class 4,5,6	0.0014(1)	0.9697	0.1626(1)	0.6867	0.7269(1)	0.3939	1.4520(1)	0.2282
LS_class 1,3,5 = LS_class 2,4,6	0.0023(1)	0.9616	0.4867(1)	0.4854	0.1982(1)	0.6562	2.7916(1)	0.0948
	Not_want_ diff_continu		Many_mistakes_ diff_continue		Working_attitude _diff_continue		Accelleration	
LS_class 1,2,3 = LS_class 4,5,6	0.3343(1)	0.5632	0.2511(1)	0.6163	0.0060(1)	0.9381	0.1747(1)	0.6760
LS_class 1,3,5 = LS_class 2,4,6	1.0279(1)	0.3106	0.4910(1)	0.4835	0.4027(1)	0.5257	0.0579(1)	0.8098
	Opinion_child _accell		Catch_up _accell		Gap_accell _diff_continue			
LS_class 1,2,3 = LS_class 4,5,6	0.7382(1)	0.3902	0.0069(1)	0.9336	1.0071(1)	0.3156		
LS_class 1,3,5 = LS_class 2,4,6	0.0143(1)	0.9050	2.7266(1)	0.0987	1.8874(1)	0.1695		

where: * represents a significant test result and df is degree of freedom

R and SAS codes

1. R code for bar charts and mosaic plots.

```
library(scales)
```

```
################Bar chart for Knowledge VS Function########
oknowledge=ordered(alldata$Knowledge, levels=c(1, 2, 3))
percentage <- table(alldata$Function, oknowledge)
percentage1<-prop.table(percentage,1)*100
barplot(percentage1, ylab="percentage",xlab="Knowledge",width=0.85,
xlim = c(0,8.5), ylim=c(0,100), col=c("darkblue","red","green"),
legend.text=c("Pre-school teacher", "Primary school teacher","remedial teacher"),
        beside=TRUE, args.legend = list(x="topleft", bty="n",cex = 0.9),axis.lty=1)
 ################Bar chart for Experience VS Function########
 oExperience=ordered(alldata$Experience, levels=c(1, 2, 3))
percentage <- table(alldata$Function, oExperience)
percentage1<-prop.table(percentage,1)*100
barplot(percentage1, ylab="frequency",xlab="Experience",width=0.85, xlim = c(0,8.5),
 ylim=c(0,300), col=c("darkblue","red","green"), legend.text=c("Pre-school teacher",
"Primary school teacher","remedial teacher"), beside=TRUE, args.legend = list(x="topleft",
bty="n",cex = 0.9), axis.lty=1)
################mosaic plot for Experience, Knowledge vs class, experience vs class######
library(stats)
mosaicplot(~ Knowledge + Experience, data = selected1,
           col=c("brown","grey"),type="pearson")
mosaicplot(Classes ~ Knowledge, data = selected1,
          col=c("black","grey","brown"),type="pearson")
mosaicplot(Classes~ Experience, data = selected1,
          col=c("black","grey","brown"),type="pearson")
```

2. SAS code for POM and PPOM

```
################POM for response Knowledge########
proc logistic data=selected1;
class function;
where knowledge NE 99;
model knowledge(descending)= function Experience_teaching Experience_care
Experience_teaching*Experience_care/link=cumlogit aggregate scale=none;
 estimate 'Function12' function 1 -1 / exp;
 estimate 'Function13' function 1  0  -1 / exp;
 estimate 'Function23' function 0  1  -1 / exp;
run;
################PPOM for response Experience########
proc logistic data=selected1;
class function;
where Experience NE 99;
model Experience(descending)= function Experience_teaching  Experience_care
Experience_teaching*Experience_care/unequalslopes=(Experience_teaching Experience_care)
 link=cumlogit aggregate scale=none;
  estimate 'Function12' function 1 -1 / exp;
```

```
  estimate 'Function13' function 1  0  -1 / exp;
  estimate 'Function23' function 0  1  -1 / exp;
run;
################SAS macro code for Emperical logit plots ########
options nomprint nomlogic;
 %macro plot(data=, gtitle=&fixed, var=, fixed=);
/* visual inspection of the proportional odds assumption */
 ods select none;
 proc freq data=&data;
     table &fixed*&var / out=os;
     run;
 proc sql noprint;
 select count(distinct &var) into: ncol from os;
 quit;
 %let ncol=&ncol;
 %*put ncol=&ncol;
    proc transpose data=os out=tran; by &fixed; var count; run;
     data a;
 set tran;
     const=0.5;
 %do i=1 %to %eval(&ncol - 1);
  %let x=%eval(&i+1);
      cummlogit&i=log((sum(of col1-col&i)+const)/(sum(of col&x - col&ncol)+const));
 %end; run;
ods select all;
ODS GRAPHICS ON/ RESET IMAGENAME = "&fixed" IMAGEFMT =JPEG;
   proc sgplot data=a;
     title "Visual inspection of the proportional odds assumption: &gtitle ";
 %do i=1 %to %eval(&ncol - 1);
  %let x=%eval(&i+5);
      series y=cummlogit&i x=&fixed/MARKERATTRS=(size=&x) MARKERS;
    %end;
     xaxis integer type=discrete DISCRETEORDER= DATA;
 yaxis values=(-5 to 5) label='Empirical cummulative logits'; run;
ODS GRAPHICS OFF;
%mend;
%plot(data=selected1, gtitle=function, var=experience, fixed=function);
%plot(data=selected1, gtitle=Experience_teaching, var=experience, fixed=Experience_teaching);
%plot(data=selected1, gtitle=Experience_care, var=experience, fixed=Experience_care);
%plot(data=selected1, gtitle=Exp_care_teaching, var=experience, fixed=Exp_care_teaching);
```

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Richting: **Master of Statistics-Biostatistics**
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Datum: **1/09/2015**