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FACULTY OF SCIENCES
Master of Statistics

Master's thesis

Research on the effectiveness of an in-depth training program for schools and parents, aimed at installing a challenging learning environment for gifted children in Belgian Schools

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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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Research on the Effectiveness of an In-Depth
Training Program for Schools and Parents, Aimed at
Installing a Challenging Learning Environment for
Gifted Children in Belgian Schools

MASTERS THESIS.



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Abstract

Giftedness is defined as having a prominent talent in a particular area (math, language, sport, etc) and also having a high IQ usually greater than 130 (Bainbridge, 2015). This talent must however be developed to avoid being an underachiever. Underachievement occurs when an individual achieves less than what is expected and this persists over a long period of time (Siegle & McCoach, 2009). In order to tackle the issue of underachievement, *Exentra vzw* organised a training program for the teachers and parents of gifted children with the goal being to accommodate the advanced cognitive and emotional development of the gifted children. There is then the need for the evaluation of the training hence this study. The study comprises of 91 teachers who attended the training program and were given the same questionnaires to fill at pre and post-training. There were 4 major sections of the questionnaire; Knowledge, Experience, Opinion and Concerns and Specific Knowledge with all the questions being the variables of interest. Proportional odds and non-proportional odds models were considered due to the ordinal nature of the dependent variables. The evolution of primary school and pre-school teachers was not different since the Function*Time interaction was not significant while that of Knowledge had a borderline significance implying there was a difference in the evolution of primary and pre-school teachers. For Opinion and Concerns, Function*Time interaction had a borderline significance on 2 dependent variables while for Specific Knowledge, Function*Time interaction had a significant effect on 5 dependent variables. Based on the results, the intervention program is already effective at the Knowledge and Experience sections but time is needed to attain effectiveness at the Opinion and Concerns and the Specific Knowledge sections.

KEYWORDS: Proportional Odds Model; Gifted children; Firth's method; Cumulative logit; Knowledge; Experience; Opinion and Concerns; Specific Knowledge.

2 Introduction

It is revealed in literature that the term *gifted child* does not have a general accepted definition because different schools come up with different definitions. However, most of the definitions have the same general idea as viewed by Bainbridge (2015) which explains giftedness as possessing a prominent talent in a particular area (maths, language, sports, arts, etc.) and also having a higher IQ ($IQ > 130$) which is an indicator of higher abilities and aptitude than their peers. The talent must be developed in order to be a high achiever by the time the child gets to adulthood. Not all gifted children develop their talents as they ought to, hence they become underachievers, meaning they do not achieve up to their abilities or IQ (NSGT, 2015).

Underachievement is considered as the extreme deviation of actual achievement (measured by grades or teacher evaluations) from the expected achievement (measured by standardized achievement test scores or cognitive or intellectual ability assessments).

One can therefore be referred to as an underachiever when underachievement exists for a long period of time and it is not as a direct result of diagnosed learning disabilities (Siegle & McCoach, 2009).

Six possible causes of underachievement include initiating situation, value conflicts, inconsistency and opposition, inappropriate classroom environment, competition and excessive power. Expatiating on each of the causes in same order as above, we have the following: Firstly, change in the initial situation of a gifted child like having a new school, divorce of parents, death of a parent (or even both), introduction of a step parent can affect the achievement of a gifted child. Secondly, underachievement results when surrounded by peers with negative attitudes because of peer influence even if the gifted child has acquired good moral lessons from parents. Thirdly, gifted children who receive contradictory messages from both teachers and parents could underachieve as a result of confusion. Fourthly, classroom environments do not really contribute much to gifted children because most already know 40 → 50% of the curriculum to be covered at the start of the academic year so they tend to be distracted, unproductive and bored of repetition. Research shows that most gifted children spend 80% of their time in normal classroom environment instead of attending specialized programs that meet their special needs. In addition, only 39% of classroom teachers have been trained to teach gifted children which is a cause for concern. Fifthly, when competition among gifted children becomes fierce, some gifted children could think it is safe to withdraw due to fear of failure because they think it is less risky not to perform than to fail hence they become underachievers. Lastly, children have a tendency to underachieve if they are given so much authority at home because they find it difficult to cope in school environments where they possess no authority. (Siegle & McCoach, 2009).

Speculations of the prevalence of underachievers among gifted children ranges from 10% to more than 50% (Siegle & McCoach, 2009). A study of 153 gifted children conducted by Peterson and Colangelo showed that 45% of them who were underachieving in grade 7 continued with the same trend at junior high and high school (Peterson & Colangelo, 1996). Peterson did a follow up study on these students, 4 years after high school, and reported that all the achievers involved in her study attended college with 83% of them completing their respected programs while 87% of the underachievers attended college and only 57% of them completed their studies (Peterson, 2000). Another longitudinal study conducted by McCall, Evahn and Kratzer showed that the professional and educational status of high school underachievers after 13 years from high school reflected their low grades obtained at high school. They also realized underachievers had a greater tendency of not completing college as well as not remaining in their jobs (McCall, Evahn & Kratzer, 1992).

Parents and teachers worry about the waste of potentials when gifted children do not achieve up to expectation. The gifted children themselves feel a loss of personal fulfillment and the nation as a whole suffers from loss of resources. Underachievement continues to be problematic to teachers and parents for the past 25 years since it is the number one issue in the field of gifted education as assessed by the National Research Center on the

Gifted and Talented (Siegle & McCoach, 2009). Underachievement can therefore be seen as a serious problem and it should be prevented or reversed if possible.

In order to tackle the problem of underachievement, an organization called *Exentra vzw* developed an ongoing multi-annual (designed for 4 years), in-depth training program for school staff and parents of gifted children. The training comprises of coaching sessions and lectures for teachers and parents and it focuses on trying to identify the needs of gifted children and also how to establish a suitable education environment for gifted children in Belgian schools. The goal of the training being to accommodate the advanced cognitive abilities and emotional development of the gifted learners by letting their teachers learn techniques on how to enrich the curricula for the gifted learners. There is need for evaluation of the effectiveness of this training which determines the establishment of the learning environment suitable for gifted children under the age of 12 in Flemish schools.

This research will therefore provide an answer as to whether the training program is already effective at the first year of its implementation. This research investigates whether there is a positive change of teachers' views towards the establishment of a suitable learning environment for gifted children after a year of training and this positive change in views would mean the training program is effective.

2.1 Objectives

To determine if there is an evolution in knowledge, experience, opinion and concerns among the teachers that attended the classical coaching sessions (with or without demographic variables) and also to determine if the level/magnitude of evolution differ between the pre-school teachers and the primary school teachers (with and without variables).

2.2 Data Description and Notations

The data includes the responses to the questions of the same questionnaire given to 91 teachers before and after one year of training by *Exentra vzw*. The questions were classified into 4 major sections namely; Knowledge (containing 1 question), Experience (containing 1 question), Opinions and Concerns (containing 18 questions) and Specific Knowledge (containing 13 questions). All the questions are dependent variables of interest. The dependent variables containing the responses to the questions are categorized as follows;

$$Y_i = \begin{cases} 1 & \text{Not} \\ 2 & \text{To a lesser extent} \\ 3 & \text{To a large extent} \end{cases} \quad (1)$$

OR

$$Y_i = \begin{cases} 1 & \text{Strongly Disagree} \\ 2 & \text{Slightly Disagree} \\ 3 & \text{Neither Agree nor Disagree} \\ 4 & \text{Slightly Agree} \\ 5 & \text{Strongly Agree} \end{cases} \quad (2)$$

OR

$$Y_i = \begin{cases} 1 & \text{Disagree} \\ 2 & \text{Neither Agree nor Disagree} \\ 3 & \text{Agree} \end{cases} \quad (3)$$

Demographic variables of interest include; *Function* which provides information on the function of each teacher either as a pre-school or a primary school teacher. The reference category for *Function* was considered to be *Pre-school teacher* (where *Function=1*) in all the models for this study *Function* is categorized as follows;

$$Function = \begin{cases} 1 & \text{Pre-school Teacher} \\ 2 & \text{Primary School Teacher} \end{cases} \quad (4)$$

School_community which contains the communities where the schools belong. The reference category for *School_community* was considered to be *Kruizinga* (where *School_community = 1*) in all models for this study. *School_community* is categorized as follows;

$$School\ Community = \begin{cases} 1 & \text{Kruizinga} \\ 2 & \text{Oudenaarde} \\ 3 & \text{Vlaamse Ardennen} \\ 4 & \text{Antwerpen} \end{cases} \quad (5)$$

T. Experience which indicates the number of years of teaching experience of each teacher. In order to capture evolution in the data, the variable *Time* was created and is categorized as follows;

$$Time = \begin{cases} 1 & \text{Before training} \\ 2 & \text{One year after training} \end{cases} \quad (6)$$

3 Methodology

3.1 Exploratory Data Analysis

Cross-tables and bar plots were used as exploratory tools to provide insight to the data. Cross-tables were produced to obtain the number of pre-school and primary school teachers in the study and also to obtain the number of teachers per community. They were also produced to have an idea on which school belongs to which community and also to have an idea on the number of pre-school and primary teachers that are found in each community. Bar plots of the dependent variables of both pre and post-training were also obtained to detect any similarities or differences of the pre and post measurements.

3.2 Proportional Odds with GEE

Proportional odds model (POM) is the chosen model for the dependent variables in the study since it takes into account their ordinality . Proportional odds models are also referred to as cumulative logit models and are one of the most popular models for responses with ordinal categories (Gameroff, 2005). It models the logit of the cumulative probabilities up to a certain response category (i.e. the cumulative probabilities of that category and lower categories) versus the cumulative probabilities of categories greater than that response category or vice versa. The logit function of the cumulative probabilities then relates to a linear function of the explanatory variables as shown below (Stiger et al., 1999);

$$\ln \left(\frac{Pr(Y \leq m)}{Pr(Y > m)} \right) = \alpha_m + X\beta \quad [1]$$

OR

$$\ln \left(\frac{Pr(Y > m)}{Pr(Y \leq m)} \right) = \alpha_m + X\beta \quad [2]$$

Where m is an ordered response category ($1 \leq m < M$), X is a vector of independent variables, α is a cut-point and β is a vector of logit coefficients.

Where $Pr(Y \leq m) = \pi_1 + \dots + \pi_m$, with $m = 1, \dots, M$
and $Pr(Y > m) = \pi_{m+1} + \dots + \pi_M$, with $m = 1, \dots, M$

where π_m is the probability that $Y = m$ for $m = 1, \dots, M$. Series of binary cumulative logits can then be defined as follows;

$$\ln \left(\frac{Pr(Y \leq m)}{Pr(Y > m)} \right) = \ln \left(\frac{\pi_1 + \dots + \pi_m}{\pi_{m+1} + \dots + \pi_M} \right) \quad [3]$$

OR

$$\ln \left(\frac{Pr(Y > m)}{Pr(Y \leq m)} \right) = \ln \left(\frac{\pi_{m+1} + \dots + \pi_M}{\pi_1 + \dots + \pi_m} \right) \quad [4]$$

with $m = 1, \dots, M$

(Fullerton & Xu, 2012)

Where all M categories are used by each cumulative logit, The proportional odds model estimates $M - 1$ cumulative logits and has as an assumption of setting all β_s equal for all the cumulative logits (Fullerton & Xu, 2012).

POM was the model of choice because the slope parameters are the same irrespective of the cumulative logit which eases interpretation. Also, the exponentiated slope parameters are interpreted as odds ratio which is applicable for many studies (Stiger et al., 1999).

Since the data had repeated measures per teacher, correlation had to be taken into account. So the quasi-likelihood generalized estimating equations (GEE) was applied to take care of the correlated data and also to correct the standard errors of the estimates. The GEE method was applied because it does not require estimations of higher order nuisance parameters, it has few distributional assumptions and even if the correlation structure is wrongly specified, the marginal estimates are still consistent, provided the marginal model is rightly specified. Maximum likelihood methods are more efficient in accounting for correlation but they are computationally difficult and they require higher order parameter estimations which are not important, so the GEE method is preferred (Stiger et al., 1999). POM with GEE was the initial considered model as described by equations [1] and [2] above. This is because we were interested in modeling the probability of being in the higher categories for some dependent variables and the probability of being in the lower categories for some dependent variables. The independence working correlation structure was considered. The POM model was run in PROC GENMOD while its proportional odds assumption was checked using the score test in PROC LOGISTIC (SAS 9.4).

3.3 Binary Logistic Regression Models for Ordinal Data with Non-proportional Odds

For the dependent variables whose proportional odds assumptions were violated, separate binary logistic regression models were used per cumulative logit, with the dependent response dichotomized at each cumulative logit as shown in equation [2] above . This

model is similar to POM with the only difference being that the slope parameters are now different per cumulative logit. 2, 3 and 4 separate binary logistic regression models were run for dependent responses with 3, 4 and 5 categories respectively in PROC GENMOD (SAS 9.4). Separate binary logistic regression was applied for these dependent responses with their final set of covariates obtained from model building as described below. The separate binary logistic regression model was considered because it is a more careful analysis and the cumulative probabilities were modeled to account for the ordinality of the dependent variables (Bender & Grouven, 1998). The working correlation structure used was the independence working correlation structure which is the same used for the POM in order to have similar standard errors as in the case of the POM.

3.4 Firth Logistic Regression

Firth logistic regression was used to replace models which did not converge in PROC GENMOD. Lack of convergence was due to small sample size of some of the binary logistic regression models and the separation phenomenon detected in some of the dependent variables. Firth's method reduces bias and produces consistent and finite estimates even when separation occurs (Wang, 2014). However, the standard errors obtained from this method could not be fully trusted since correlation due to subject repeated measures was not taken into account hence no correction of standard errors. Firth's method was applied via PROC LOGISTIC (SAS 9.4).

3.5 Model Building

While considering the POM model, a backward selection model building was done on the saturated model which included all covariates of interest, meaningful interactions, time covariate and the interaction of covariates with time. The saturated model was as follows;

$$Y = \beta_1 Function + \beta_2 School_community + \beta_3 T.Experience + \beta_4 Time + \beta_5 Function*Time + \beta_6 School_community*Time + \beta_7 T.Experience*Time + \beta_8 Function*T.Experience$$

Where Y= dependent variable

The model building process was applied first on the interactions of covariates and covariates with time. The interaction with the highest insignificant p-value was dropped and the QIC (Quasi-Akaike Information Criteria) was checked if it reduces or increases because the lower the QIC, the better the fit of the model. If QIC decreases after dropping the interaction, then the interaction is left out and the procedure continues until all insignificant interactions which lower the QIC on their removal are dropped out of the model. Model building is first done on the interactions because if an interaction is found significant, its main effects have the chance to be retained in the model even if they are

insignificant.

The interaction of Function and Time was always retained in the model whether it is significant or not because it is linked to the objective of the study. The same backward selection procedure as described above was applied on the main effects to obtain the most appropriate model with the best fit (lowest QIC value). Main effects with significant interactions were retained in the model irrespective of their significance. The covariates Function and Time were also included in the model because they are linked to the objectives of the study. GEE models obtain their estimates via the quasi-likelihood function and not the full likelihood hence the AIC approach for model selection does not apply to GEE models. Therefore, QIC which was developed for GEE models, is an equivalent of AIC (Akaike Information Criteria) for full likelihood models. QIC was then used for model building. QIC strikes a balance between the complexity of the model and its fit and it chooses the best parsimonious GEE model (Hocking, 2012).

3.6 Softwares Used

R 3.1.3 was used to produce the bar plots of the dependent variables at exploratory data analysis. SAS 9.4 was used to produce frequency tables, model building, model fitting and the Firth's method.

4 Results and Discussion

4.1 Exploratory Data Analysis

A total of 91 teachers (33 pre-school and 58 primary school teachers) from 27 schools were involved in the training program of which 89 were females and 2 were males. A range of 1-8 teachers were selected from each of the 27 schools to participate in the training program with 3 teachers selected from most schools as seen in the appendix (table 9).

Kruizinga, Oudenaarde, Vlaamse Ardennen and Antwerpen were the 4 communities where the schools were chosen for this study. From the Kruizinga community, 7 schools were selected with a total of 20 teachers, 10 schools with 35 teachers were selected from the Oudenaarde community, 6 schools with 16 teachers were selected from the Vlaamse Ardennen community and 4 schools with 20 teachers were selected from the Antwerpen community. A cross-table of the above results is provided in the appendix (table 9).

The table below (table 1) shows the number of pre and primary school teachers per community. It can be seen that for all the communities, fewer pre-school teachers than primary school teachers were selected for the training.

Table 1: *Cross-table showing the number of pre and primary school teachers per community*

Function	School community				Total
	Kruizinga	Oudenaarde	Vlaamse Ardennen	Antwerpen	
Pre-school teacher	6	12	6	9	33
Primary school teacher	14	23	10	11	58
Total	20	35	16	20	91

Teachers involved in this study had a range of 0-9 gifted children in their teaching classes with 7 teachers having no idea if gifted children were found in their classes. A few number of teachers (5) had no gifted child in their classes so this study directly involved majority of the teachers since 79 of the teachers had at least 1 gifted child in their teaching classes. Teaching experience of the teachers ranged from 1-34 years.

4.1.1 Knowledge

Knowledge is one of the four major sections of the questionnaire filled by the teachers before and after one year of training. It contains one question which is a dependent variable of interest. The detail of the question is found in the appendix. The bar plots of this dependent variable of interest pre and post-training are as shown in figure 1 below

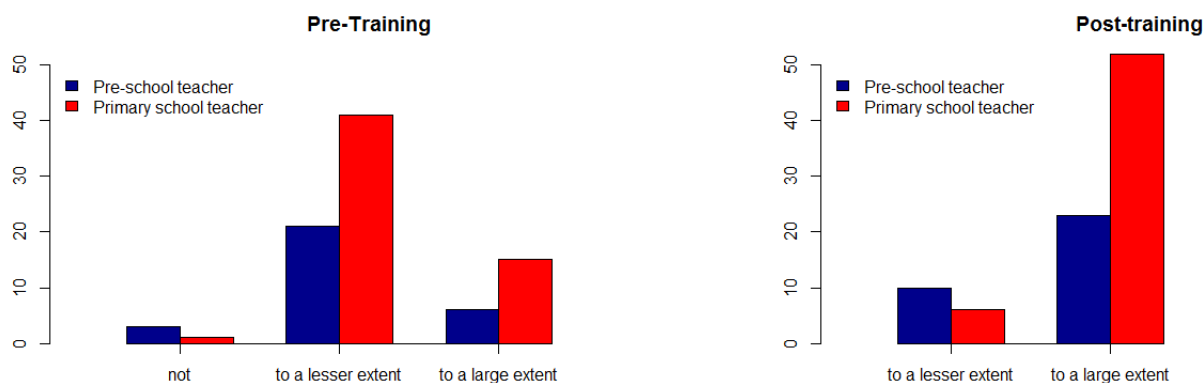


Figure 1: *Barplots for knowledge at pre and post-training*

From figure 1 above, the teachers seem to have an increase in the extent of knowledge about the educational adaptations for gifted children after one year of training because at post-training, the number of teachers at the "to a large extent" category seem to be higher than that of the pre-training. Also, there seem to be a shift towards the larger extent knowledge category when moving from pre to post-training with no "not" category

at post-training. There seem to be a higher number of primary school teachers at the "to a large extent" category at post-training than pre-school teachers suggesting more primary school teachers believed they had an increased extent of educational adaptation for gifted children than pre-school teachers at post-training.

4.1.2 Experience

Experience is another major section of the questionnaire which contains one dependent variable of interest. The question concerning experience is found in the appendix. The pre and post-training bar plots of the dependent variable are shown in figure 2 below

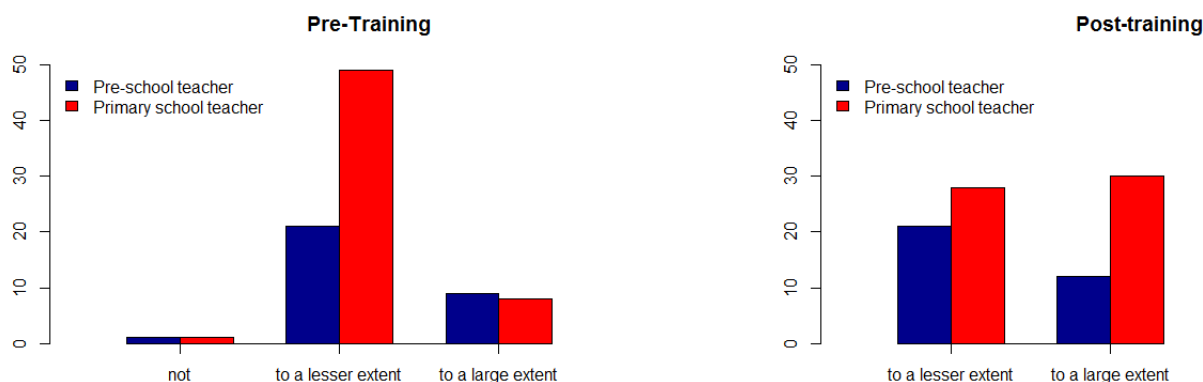
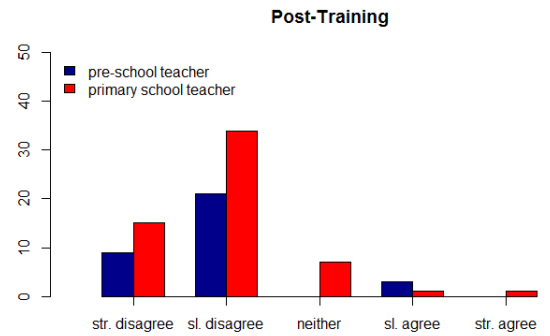
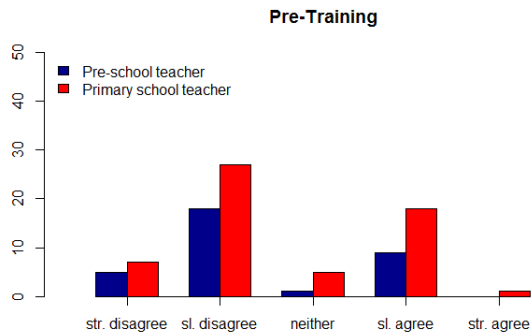


Figure 2: *Barplots of Experience at pre and post-training*

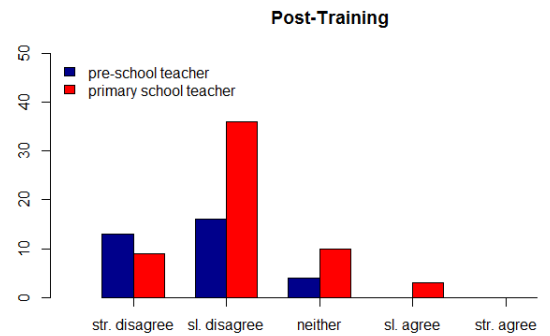
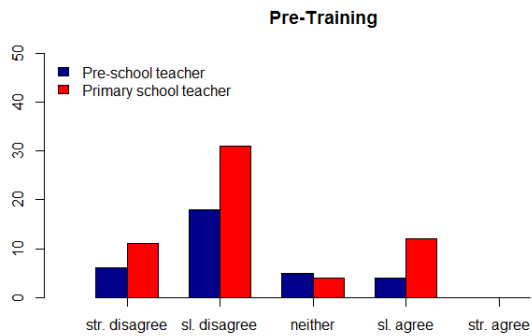
It is seen from figure 2 that at post-training, there seem to be a drop in number of primary school teachers at the "to a lesser extent" category and there also seem to be an increase in the number of teachers at the "to a large extend" category. There is also the absence of the "not" category. All of these suggest that some of the teachers became aware of the fact that they were experienced in applying educational adaptations at a large extend at the end of the one year training with more primary school teachers having the awareness than pre-school teachers.

4.1.3 Opinion and concerns

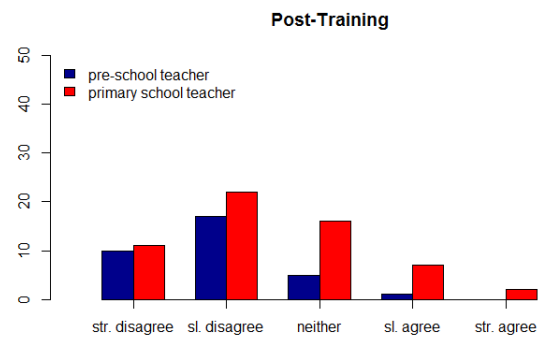
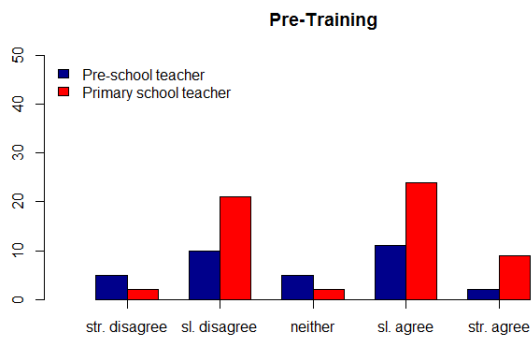
Opinion and concerns is the third major section of the questionnaire and this section contains 18 questions which are dependent variables (details of the questions and their corresponding dependent variables are found in the appendix). The bar plots of 3 of the dependent variables suggest a difference of the pre and post answers to the 3 questions. The bar plots are as shown below.



(a) Not_confident



(b) Vain



(c) Not_feasible_differentiation

Figure 3: Barplots of (a)Not_confident (b)Vain (c)Not_feasible_differentiation at pre and post-training

Figure 3 above presents the bar plots of the variables *Not_confident*, *Vain* and *Not_feasible_differentiation* at pre and post-training. There seem to be a difference in the pre-training barplots and the post-training barplots of all 3 dependent variables. For

all 3 dependent variables at post-training, the number of teachers seem to increase in the disagree categories while the number of teachers seem to drop in the agree categories hence more teachers at the disagree categories. These suggest the following at post-training .

Firstly, more teachers than before would feel confident enough to apply educational adaptations to gifted children with majority being the primary school teachers. Secondly, more teachers than before would disagree that gifted children will become vain because of educational adaptations with primary school teachers being the majority. Lastly, more teachers than before would disagree that individual differentiation for gifted children is not feasible with majority being the primary school teachers. All of these were suggested to happen at post-training.

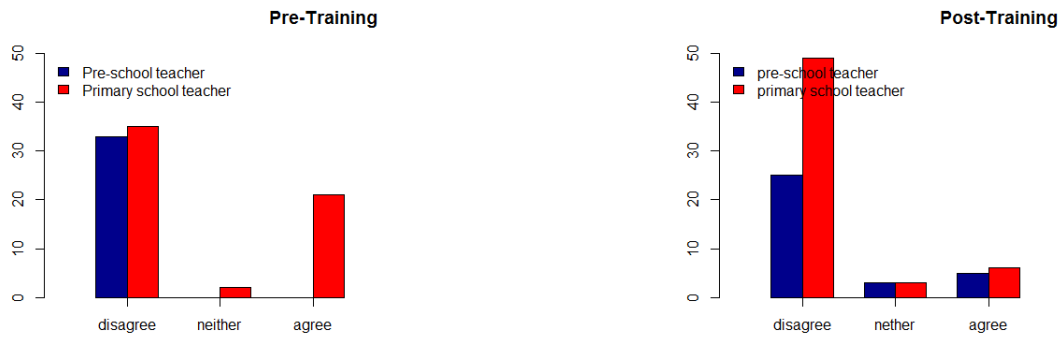
The bar plots of the other 15 questions suggest slight difference between pre and post-training (see appendix). The slight difference could be due to the change in one, two or three categories while the other categories remain fairly the same and not like the cases above where there seem to be an increase in the disagree categories with a simultaneous decrease in the agree categories or vice versa.

4.1.4 Specific Knowledge

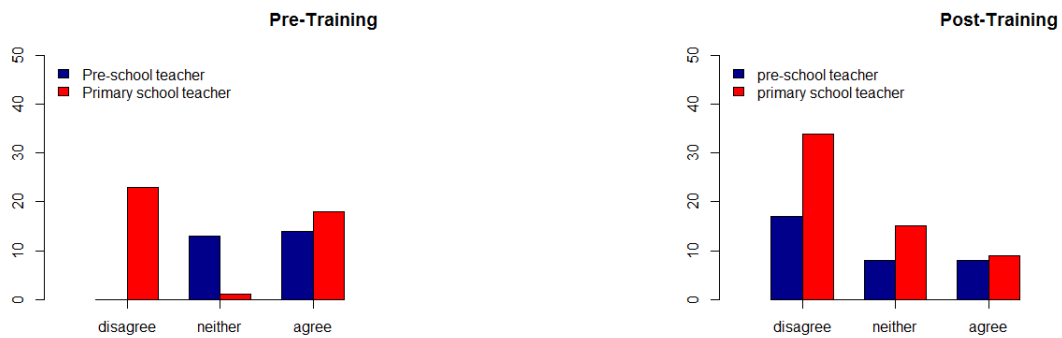
Specific Knowledge is the last major section of the questionnaire which is made up of 13 questions which are dependent variables in this study (see appendix for the questions and corresponding dependent variables). Bar plots revealed that there seem to be differences between the pre and post-training answers to 5 of the questions. The bar plots are presented below.



(a) Extra_basic_differentiation



(b) Same_assignments_differentiation



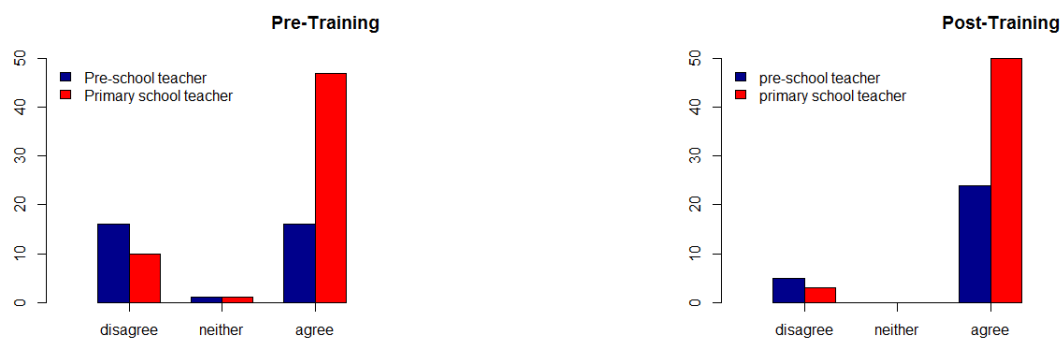
(c) Catch_up_accell

Figure 4: Pre and post-training Barplots of
 (a) Extra_basic_differentiation
 (b) Same_assignments_differentiation
 (c) Catch_up_accell

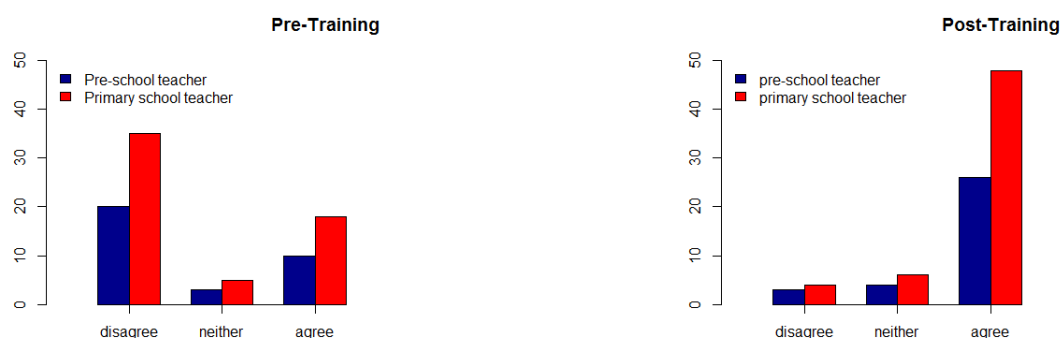
Figure 4 above presents the bar plots at pre and post-training of the variables *Ex-*

tra_basic_differentiation, *Same_assignments_differentiation* and *Catch_up_accell*. For all 3 dependent variables, it is observed that at post training, the teachers at the "agree" category seem to decrease in number while teachers at the "disagree" category seem to increase in their number. Most of the pre-school teachers seem to move to the "disagree" category at post-training for *Extra_basic_differentiation* while few pre-school teachers seem to drop from the "disagree" category at post-training for *Same_assignments_differentiation*. These suggest the following at post-training.

Firstly, most pre-school teachers would change their point of views by disagreeing to the fact that they would offer more basic exercises when the gifted child has completed his basic assignments. Secondly, most teachers would disagree that gifted children are required to complete same assignments as the other children in class. Lastly, most teachers would disagree that it is important a gifted child should catch up on the missed subjects of the skipped grade before the next school year begins. All these happen at post-training.



(a) Eliminate_differentiation



(b) Mandatory_differentiation

Figure 5: Barplots of pre and post-training of (a)Eliminate_differentiation (b)Mandatory_differentiation at pre and post-training

Figure 5 depicts the barplots of the variables "Eliminate_differentiation" and "Manda-

tory_differentiation" at pre and post-training. For both dependent variables, it is observed that at post-training, the number of teachers in the "disagree" category seem to reduce in number while the number of teachers increases in the "agree" category. These suggest the following at post-training.

Firstly, most teachers would agree to the fact that they would eliminate the already mastered curriculum of the gifted child and replace it with challenging exercises. Secondly, most teachers would agree to mandate the gifted child to work on the enrichment activities. All these happen at post-training.

For the 8 remaining questions, the barplots at pre and post-training seem to be similar hence suggesting slight difference between both plots (see appendix). The slight difference could be due to change in one or two categories while the other categories fairly remained the same.

4.2 Fitted Models

4.2.1 Knowledge

The table below provides the parameter estimates and their respective standard errors and P-values of the POM with knowledge as the dependent variable. Knowledge has 3 ordered categories with the lowest to the highest being "not", "to a lesser extent" and "to a large extent". The P-value for the score test of proportional odds assumption was 0.34 which indicates that the proportional odds assumption was not violated.

Table 2: *Parameter estimates of POM with knowledge as the dependent variable*

Parameter	Estimate	Std Error	P-value
Intercept3 [P(Y=3)]	-6.19	1.81	0.0006
Intercept2 [P(Y≥ 2)]	-1.85	1.94	0.3408
Function	0.18	1.31	0.8897
T. Experience	0.10	0.06	0.1223
Time	4.47	1.08	<.0001
Function*Time	0.45	0.82	0.5831
T. Experience*Time	-0.09	0.04	0.0237

The results in table 2 reveal that, the odds of a primary school teacher of choosing the highest category of knowledge ("to a large extent") compared to the other categories at post-training is 125 times ($e^{4.47+0.45-0.09}$) that of the odds of the primary school teacher of choosing the highest category compared to the other categories of knowledge at pre-training (odds ratio = 125.2). The odds of a pre-school teacher of choosing the highest category compared to the other categories at post-training is approximately 80 times ($e^{4.47-0.09}$) that of the odds of the pre-school teacher of choosing the highest category

compared to the other categories at pre-training (odds ratio=79.83). At post-training and given same teaching experience (keeping the interaction of T. Experience*Time constant), the odds of a primary school teacher of choosing the highest category compared to the other categories of knowledge is approximately three times ($e^{0.18+2(0.45)}$) the odds of a pre-school teacher of choosing the highest category of knowledge (odds ratio = 2.94). These imply that, at post-training, more primary and pre-school teachers chose the "to a greater extent" category of knowledge with relatively more of the primary school teachers of same teaching experience choosing the larger extend of knowledge about the educational adaptations for gifted children than pre-school teachers. The significant effect of T. Experience indicates that there is a difference of the effect of teaching experience on Knowledge at pre and post-training (P-value < 0.0237).

4.2.2 Experience

Table 3 below provides the parameter estimates and their respective standard errors and P-values of POM with Experience as the dependent variable. Experience has 3 ordered categories which are the same as those for Knowledge described above. Proportional odds assumptions were not violated as indicated by the P-value of the score test (0.71).

Table 3: *Parameter estimates of POM with Experience as the dependent variable*

Parameter	Estimate	Std. Error	p-value
Intercept3 [P(Y=3)]	-0.89	0.96	0.3544
Intercept2 [P(Y≥ 2)]	4.69	1.30	0.0003
Function	-2.24	1.17	0.055
Teaching Experience	-0.03	0.02	0.197
Time	0.42	0.50	0.3993
Function*Time	1.36	0.67	0.0417

Based on the results in table 3 above, the odds of a primary school teacher of choosing the highest category compared to the other categories of knowledge at post training is approximately 6 times ($e^{0.42+1.36}$) the odds of the primary school teacher of choosing the highest category compared to the other categories of knowledge at pre-training (odds ratio=5.93). At post-training, the odds of a primary school teacher of choosing the highest category ("to a greater extent") compared to other categories of Experience is approximately twice ($e^{-2.24+2(1.36)}$) that of a pre-school teacher of same teaching experience (odds ratio = 1.62). These imply that more primary school teachers chose the "to a greater extent" category of knowledge at post training. It also revealed that more of the primary school teachers chose the "to a greater extent" category than pre-school teachers at post training.

4.2.3 Opinion and Concerns

The table below provides estimates for the two cumulative logits of a non proportional odds model with acceleration as the dependent variable. It is a non proportional odds model because its proportional odds assumption was violated (p-value = <.0001). The estimates below were obtained from binary logistic regression of the two separate cumulative logits. Acceleration has three categories which exist in an ascending order as follows; "disagree" , "neither disagree nor agree" and "agree". The results for the other models of the dependent variables in the opinion and concerns section are found in the appendix except that for Convinced_benefit which did not converge.

Table 4: *Parameter estimates of two cumulative logits of a Non proportional odds model with Acceleration as the dependent variable*

Parameter	P(Y=3)			P(Y≥ 2)		
	Estimate	Std. Error	P-value	Estimate	Std. Error	P-value
Intercept	8.86	1.87	<.0001	3.73	2.15	0.0824
Function	0.63	0.97	0.5137	-0.77	1.36	0.5685
Oudenaarde	-2.40	1.43	0.0927	0.61	1.57	0.697
V. Ardenen	-3.67	1.55	0.0182	-2.26	1.73	0.1918
Antwerpen	-5.93	1.55	0.0001	-3.49	1.75	0.0458
Teaching Experience	-0.21	0.06	0.0004	-0.07	0.07	0.2557
Time	-7.08	1.30	<.0001	-1.06	1.33	0.4258
Function * Time	-0.83	0.62	0.1804	-0.16	0.92	0.8609
Oudenaarde*Time	2.41	0.99	0.0147	-0.18	0.90	0.8368
V. Ardenen*Time	3.28	1.04	0.0016	1.50	1.12	0.1796
Antwerpen*Time	5.57	1.14	<.0001	2.72	1.22	0.0254
Teaching Experience*Time	0.18	0.04	<.0001	0.04	0.04	0.3172

The results of the logit P(Y=3) in table 4 above reveal that at post-training, given that the teachers are from the kruizinga school community and same teaching experience, the odds of a pre-school teacher of choosing the "agree" category compared to the other categories of Acceleration is approximately 3 times ($e^{1.66-0.63}$) the odds of a primary school teacher of choosing the same "agree" category compared to the others (odds ratio = 2.8).

The results of the logit P(Y≥2) in table 4 above reveal that at post-training, given that the teachers are from the kruizinga school community and same teaching experience, the odds of a pre-school teacher of choosing either the "agree" or the "neither agree nor disagree" categories compared to the "disagree" category of Acceleration is approximately three times ($e^{0.77+0.32}$) the odds of a primary school teacher of choosing the same "agree" category compared to the others (odds ratio = 2.97).

However, only the cumulative logit of being in the "agree" category [logit P(Y=3)] will be interpreted due to the objectives of the research. It was of interest to model the "agree" category versus the "disagree" and "neither disagree nor agree" to get the probability of

the shift towards the "agree" category. The parameter estimates from both cumulative logits were not similar which is an indication that a non proportional model was suitable to model the dependent variable Acceleration.

The table below (Table 5) provides the estimates, standard errors and P-values of the covariate Time and the interaction of Function and Time of the dependent variables found the opinion and concerns section of the questionnaire. It is the interest of the research that the table below is provided in order to have an idea of the dependent variables where there was a difference in evolution between the primary and pre-school teachers. However, Time should not be interpreted independently since it interacts with other covariates. The estimates, standard errors and P-values are as shown below;

Table 5: *Time and Function*Time estimates (standard errors in braces and their respective p-values) of dependent variables in the opinion and concerns section of the questionnaire*

Dependent Variable	Time		Time*Function	
	Estimate	P-value	Estimate	P-value
Difficult_to_detect	1.10 (0.36)	0.0024	-0.64 (0.48)	0.1885
Overburdened	-2.08 (1.71)	0.2229	0.76 (0.98)	0.4369
Not_confident	1.51 (0.80)	0.057	-0.10 (0.89)	0.9146
Fear_of_failure	1.32 (0.62)	0.0336	-1.32 (0.79)	0.0925
Being_a_child	-0.23 (0.98)	0.8135	0.734 (0.70)	0.2936
Outside_of_school	4.00E-15 (0.93)	1.000	3.45 (1.72)	0.0452
Parents_pressure	-3.15 (1.29)	0.0146	0.33 (0.73)	0.6521
Colleagues_not_open	-0.88 (0.44)	0.0457	-0.91 (0.57)	0.113
Resources_weaker_children	-0.31 (0.48)	0.5262	-0.41 (0.63)	0.5103
Long_term_effect	-1.76 (1.16)	0.1283	0.58 (1.39)	0.6774
Vain	1.1 (0.54)	0.0405	-0.85 (0.63)	0.1796
Not_feasible_differentiation	1.70 (0.49)	0.0005	-0.97 (0.60)	0.1078
Extra_time_differentiation	0.12 (0.44)	0.7814	-0.82 (0.64)	0.2023
Less_time_differentiation	0.00 (0.34)	1.000	-0.58 (0.48)	0.2286
Ache_for_differentiation	-0.20 (0.76)	0.7952	0.71 (0.70)	0.3113
Selfesteem_pullout	-0.31 (0.53)	0.5632	-1.36 (0.70)	0.0496
Acceleration	-7.08 (1.30)	<.0001	-0.83 (0.62)	0.1804

It is observed that there is a difference in evolution between primary school and pre-school teachers in 2 dependent variables since their Time*Function effect is significant (P-values < 0.05).

4.2.4 Specific Knowledge

The table provides estimates of the non proportional odds model with *Not-Want-Diff-Continu* as the dependent variable. *Not-Want-Diff-Continu* has five ordered categories

with the lowest to the highest category being "strongly disagree", "slightly disagree", "neither disagree or agree", "slightly agree" and "strongly agree". Proportional odds assumption was violated (P-value < 0.0001) so each of the four separate cumulative logits was modeled via a binary logistic regression and the estimates obtained as shown on Table 6 below. The results of the other dependent variables found in Specific Knowledge section of the questionnaire are found in the appendix except *Same_assignments_differentiation*, *Challenging_differentiation* and *Gap_accell* which failed to converge.

Table 6: *Parameter estimates with standard errors in braces of four cumulative logits of a Non proportional odds model with Not-Want-Diff-Continu as the dependent variable*

Parameter	P(Y=5)		P(Y≥ 4)		P(Y≥ 3)		P(Y≥ 2)	
	Estimate	P-value	Estimate	P-value	Estimate	P-value	Estimate	P-value
Intercept	-4.59 (4.62)	0.321	-0.84 (1.07)	0.4333	-1.57 (1.19)	0.1855	2.43 (3.17)	0.444
Function	-3.18 (3.71)	0.3914	-1.72 (0.91)	0.0576	-2.15 (0.96)	0.0247	0.59 (3.40)	0.8627
T. Experience	0.07 (0.20)	0.7125	0.10 (0.05)	0.0301	0.11 (0.05)	0.0388	0.09 (0.15)	0.5624
Time	0.88 (2.68)	0.7416	0.60 (0.64)	0.3556	1.09 (0.78)	0.1637	-0.16 (1.87)	0.931
Function* Time	2.57 (2.24)	0.2512	1.78 (0.58)	0.0023	2.29 (0.65)	0.0005	1.20 (2.11)	0.5715
T. Experience*time	-0.08 (0.11)	0.4861	-0.09 (0.03)	0.0031	-0.07 (0.04)	0.0372	-0.06 (0.09)	0.5142

From table 6 above, the parameter estimates of the cumulative logits P(Y=5) and P(Y≥ 2) were obtained via the Firth method because of lack of convergence. Their parameter estimates had no significant effect since all the P-values of their estimates were greater than 0.05. However the standard errors of their parameter estimates could not be trusted since correlation of repeated measures was not taken into account.

For the logit P(y≥ 4), the odds of a primary school teacher of choosing either of the agree categories compared to the other categories of the dependent variable at post-training is 10 times ($e^{0.6+1.78-0.09}$) the odds of the teacher choosing either of the higher categories compared to the other categories at pre-training (odds ratio = 9.87). The odds of a pre-school teacher of choosing either of the agree categories compared to the other categories of the dependent variable at post-training is 2 times ($e^{0.6-0.09}$) the odds of the teacher choosing either of the higher categories compared to the other categories at pre-training (odds ratio = 1.66). At post-training and given same teaching experience, the odds of a primary school teacher of choosing one of the agree categories compared to the other categories of the dependent variable is 6 times ($e^{-1.72+2(1.78)}$) the odds of a pre-school teacher of choosing one of the agree categories compared to the other categories of the dependent variable (odds ratio = 6.3). These imply there is a tendency for more teachers to choose either one of the agree categories with primary school teachers having a relatively slightly higher tendency than pre-school teachers in choosing those categories.

For the logit P(y≥ 3), the odds of a primary school teacher of choosing either of the agree categories or the "neither agree nor disagree categories" compared to the other categories of the dependent variable at post-training is 27 times ($e^{1.09+2.29-0.07}$) the odds of the teacher choosing either of the higher categories or the "neither agree nor disagree" category compared to the other categories at pre-training (odds ratio = 27.39). The

odds of a pre-school teacher of choosing either of the agree categories or the "neither agree nor disagree" category compared to the other categories of the dependent variable at post-training is approximately 3 times ($e^{1.09-0.07}$) the odds of the teacher choosing either of the higher categories of the "neither agree nor disagree" category compared to the other categories at pre-training (odds ratio = 2.8). At post-training and given same teaching experience, the odds of a primary school teacher of choosing either one of the agree categories or choosing the "neither agree nor disagree" category compared to the other categories of the dependent variable is 11 times ($e^{-2.15+2(2.29)}$) the odds of a pre-school school of choosing either one of the agree categories or the "neither agree nor disagree" category compared to the other categories of the dependent variable (odds ratio = 11.36). These imply there is a tendency for more teachers to choose either the "neither agree nor disagree" category or agree categories with primary school teachers having a relatively slightly higher tendency than primary school teachers in choosing those categories.

However, only logit $P(y \geq 4)$ is of importance in this study since it is of interest to model the cumulative probabilities of the agree categories in order to have an idea of the shift towards the agree categories at post training.

The table below (Table 7) provides the estimates, standard errors and P-values of the covariate Time and the interaction of Function and Time of the dependent variables found in the specific knowledge section of the questionnaire. It is the interest of the research that the table below is provided in order to have an idea of the dependent variables where there was a difference in evolution between the primary and pre-school teachers. However, Time should not be interpreted independently since it interacts with other covariates. The estimates, standard errors and P-values are as shown below;

Table 7: *Time and Function*Time estimates (standard errors in braces and their respective p-values) of dependent variables in the specific knowledge section of the questionnaire*

Dependent Variable	Time		Time*Function	
	Estimate	P-value	Estimate	P-value
Nice_to_have_differentiation	1.41 (0.71)	0.049	0.80 (0.52)	0.1214
Choose_differentiation	0.98 (0.44)	0.0242	-1.23 (0.57)	0.032
Eliminate_differentiation	1.04 (0.47)	0.0276	-0.66 (0.68)	0.3323
Mandatory_differentiation	2.49 (0.46)	<.0001	0.32 (0.62)	0.6114
Not_want_diff_continu	0.60 (0.64)	0.3556	1.78 (0.58)	0.0023
Many_mistakes_diff_continue	-1.26 (0.53)	0.0174	1.70 (0.64)	0.0078
Working_attitude_diff_continu	-0.69 (0.63)	0.28	0.56 (0.73)	0.4394
Opinion_child_accell	2.35 (0.93)	0.0117	-0.93 (0.72)	0.1946
Catch_up_accell	4.08 (1.49)	0.0061	-3.92 (1.55)	0.0112
Extra_basic_differentiation	3.48 (0.68)	<.0001	-2.30 (0.89)	0.0095

From table 7 above, it is observed that evolution differed between primary and pre-school teachers in 5 of the dependent variables.

5 Conclusion and Recommendations

The intervention program provided by *Exentra vzw* for the gifted children can be said to be effective already for the Knowledge and Experience part of the questionnaire since there was evolution of the teachers point of views to the desired categories of the responses at post-training. However, for Opinion and Concerns and the specific Knowledge sections, there is need for improvement of these sections in order to achieve the goal of evolution of the teachers point of views towards the desired categories for almost all dependent variables. These could be achieved if the intervention program goes on over time. Since it is just a year of the intervention program, the results obtained are promising towards attaining their goal of establishing a suitable learning environment for gifted children in Belgium.

For future study of this research, an increase in sample size of the teachers is suitable in order to avoid problems of convergence when fitting models to the data.

Partial proportional odds which is an alternative to the Non-proportional odds model should be considered for future study if Proportional odds assumptions fail. Partial proportional odds model is a model which assumes the proportional odds assumption for a subset of covariates in the model and relaxes the proportional odds assumption for the other subset of covariates therefore assuming the same slope parameter for every cumulative logit for some subset of covariates while assuming different slope parameters for a subset of covariates.

6 References

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7 Appendix

7.1 Tables

Table 8: Response variables and their corresponding questions

Section	Variable name	Questions
Knowledge (EA)	Knowledge	To what extend do you have knowledge about the educational 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 colleagues 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 differentiation 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 of 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_differentiation	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_differentiation	I consider challenging excercises as 'nice to have' but not 'mandatory' for the gifted child.
Specific knowledge (Diff)	Same_assignments_differentiation	Gifted children are required to complete the same assignments as the other children in the class.
Specific knowledge (Diff)	Choose_differentiation	I would let a gifted child choose its own challenging assignments.
Specific knowledge (Diff)	Eliminate_differentiation	I would eliminate the already mastered curriculum of the gifted child and would replace it with challenging excercises.
Specific knowledge (Diff)	Challenging_differentiation	I would offer challenging excercises, when the gifted child is ready with its basis assignments.
Specific knowledge (Diff)	Mandatory_differentiation	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_continu	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 acceleration.
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 acceleration when the gifted child shows a 'gap' in its knowledge at the beginning of the new school year.

Where: *EA* = Educational adaptation, *Diff* = Diffrentaitaion, *Acce* = Acceleration

Table 9: *Cross-table showing the number of selected teachers and the schools per community*

School Community	School	Selected Teachers
Kruizinga	Kruishoutem	3
	Huise	3
	Ouwegem	3
	De Regenboog	3
	Asper	3
	Dol-fijn	3
	Gavere-Semmerzake	2
	Total	20
Oudenaarde	Bevere	4
	Eine	3
	Leupegem-Melden	2
	Ename	2
	College	3
	Mater-Welden	4
	Sint-Walburga/Pamele	3
	Nederename	3
	KBO Sint-Jozef	8
	KBO Volkegem	3
	Total	35
Vlaamse Ardennen	Petegem-Elsegem	3
	Maarkedal	3
	Etikhove	1
	Wortegem	3
	Ruien	2
	Berchem	4
	Total	16
Antwerpen	Parkschool Ieperman	5
	Sinte Maarten	3
	De Brug	6
	Sint Clara	6
	Total	20

7.1.1 Model Results for dependent variables in the opinion and concerns section

Table 10: *Parameter estimates of the proportional odds model with Difficult_to_detect as the dependent variable.*

Parameter	Estimate	Std. Error	P-value
Intercept1 [P(Y=1)]	-4.66	0.77	<.0001
Intercept2 [P(Y≤2)]	-2.08	0.66	0.0017
Intercept3 [P(Y≤3)]	-1.55	0.65	0.0175
Intercept4 [P(Y≤4)]	0.82	0.67	0.2163
Function	0.92	0.85	0.2791
Time	1.10	0.36	0.0024
Function*Time	-0.64	0.48	0.1885

Table 11: *Parameter estimates (with standard errors in braces) of the non-proportional odds model with Overburdened as the dependent variable. Parameter estimates of Logit $P(Y \leq 2)$, Logit $P(Y \leq 3)$ and Logit $P(Y \leq 4)$ were obtained via Firth's method. For this research, only parameters of Logit $P(Y \leq 2)$ should be interpreted even though the standard errors are not trusted since correlation was not taken into account.*

Parameter	P(Y=1)		P(Y≤2)		P(y≤3)		P(Y≤4)	
	Estimate	P-value	Estimate	P-value	Estimate	P-value	Estimate	P-value
Intercept	2.68 (1.42)	0.0597	6.53 (3.19)	0.0406	4.33 (3.19)	0.1747	5.20 (3.78)	0.168
Function	1.27 (0.95)	0.1784	-1.03 (1.55)	0.5062	0.39 (1.71)	0.821	-3.25 (2.89)	0.261
Oudenaarde	-1.75 (1.38)	0.2049	-4.01 (3.09)	0.1941	-3.36 (3.16)	0.2866	1.69 (4.04)	0.6757
Vlaamse Ardennen	-0.73 (1.82)	0.69	-2.88 (3.52)	0.4127	-3.40 (3.68)	0.3569	-0.38 (4.29)	0.9295
Antwerpen	-3.53 (1.44)	0.0143	-5.24 (3.53)	0.1379	-4.29 (3.51)	0.2215	-2.65 (3.67)	0.4699
T. Experience	-0.03 (0.02)	0.1268	-0.03 (0.03)	0.2484	0.003 (0.03)	0.9288	0.02 (0.05)	0.7321
Time	-2.00 (1.04)	0.055	-2.08 (1.71)	0.2229	-0.99 (1.81)	0.5846	-1.43 (2.23)	0.5205
Function*Time	-0.86 (0.62)	0.1664	0.76 (0.98)	0.4369	-0.13 (1.17)	0.9094	2.45 (1.80)	0.1748
Oudenaarde*Time	1.58 (0.97)	0.1049	1.84 (1.70)	0.2812	1.68 (1.82)	0.3561	-1.09 (2.43)	0.6543
Vlaamse Ardennen*Time	0.82 (1.29)	0.5244	1.43 (2.01)	0.4756	2.05 (2.33)	0.3786	0.12 (2.74)	0.9655
Antwerpen*Time	2.89 (0.99)	0.0039	3.38 (2.23)	0.1293	2.70 (2.24)	0.2277	1.52 (2.48)	0.5412

Table 12: *Parameter estimates (with standard errors in braces) of the non-proportional odds model with Not_confident as the dependent variable. Parameter estimates of Logit $P(Y \leq 4)$ were obtained via Firth's method. For this research, only parameters of Logit $P(Y \leq 2)$ should be interpreted.*

Parameter	P(Y=1)		P(Y≤2)		P(Y≤3)		P(Y≤4)	
	Estimate	P-value	Estimate	P-value	Estimate	P-value	Estimate	P-value
Intercept	-1.42 (1.09)	0.1942	0.38 (1.25)	0.7635	0.47 (1.28)	0.7165	5.01 (3.33)	0.1329
Function	-0.60 (1.33)	0.655	-0.65 (1.27)	0.6111	-1.78 (1.51)	0.2375	-0.74 (3.55)	0.8347
T. Experience	-0.06 (0.02)	0.0095	-0.05 (0.02)	0.0125	-0.04 (0.02)	0.0726	-0.04 (0.06)	0.45
Time	0.78 (0.62)	0.2073	1.51 (0.80)	0.057	1.35 (0.79)	0.0888	1.45E-14 (1.94)	1.00
Function*Time	0.19 (0.76)	0.8007	-0.10 (0.89)	0.9146	1.32 (1.14)	0.2469	-1.47E-14 (2.24)	1.00

Table 13: *Parameter estimates (with standard errors in braces) of the non-proportional odds model with Fear_of_failure as the dependent variable. For this research, only parameters of Logit $P(Y \leq 2)$ should be interpreted*

Parameter	P(Y=1)		P(Y≤2)		P(Y≤3)	
	Estimate	P-value	Estimate	P-value	Estimate	P-value
Intercept	-1.36 (0.98)	0.1642	-0.46 (0.93)	0.6202	-1.58 (1.08)	0.1432
Function	1.05 (1.12)	0.3488	1.77 (1.13)	0.1177	2.61 (1.58)	0.0989
Time	0.63 (0.54)	0.2464	1.32 (0.62)	0.0336	2.33 (0.96)	0.0155
T. Experience	-0.03 (0.02)	0.1939	0.01 (0.02)	0.7718	0.02 (0.03)	0.4902
Function*Time	-1.13 (0.69)	0.1045	-1.32 (0.79)	0.0925	-1.36 (1.31)	0.2977

Table 14: *Parameter estimates (with standard errors in braces) of the non-proportional odds model with Being_a_child as the dependent variable. Parameter estimates of Logit $P(Y \leq 4)$ were obtained via the Firth's method. For this research, only parameters of Logit $P(Y \leq 2)$ should be interpreted.*

Parameter	P(Y=1)		P(Y≤2)		P(Y≤3)		P(Y≤4)	
	Estimate	P-value	Estimate	P-value	Estimate	P-value	Estimate	P-value
Intercept	-3.04 (1.40)	0.0296	0.97 (1.57)	0.5425	-0.34 (1.73)	0.8456	-2.13 (3.46)	0.5389
Function	0.65 (1.06)	0.5391	-1.47 (1.16)	0.2069	-2.64 (1.30)	0.0418	1.22 (2.57)	0.6357
T. Experience	0.16 (0.06)	0.0062	0.07 (0.06)	0.2525	0.11 (0.07)	0.1322	0.19 (0.15)	0.1893
Time	1.28 (0.93)	0.1675	-0.23 (0.98)	0.8135	0.78 (1.21)	0.5201	3.75 (2.85)	0.1876
Function*Time	-0.57 (0.72)	0.4321	0.74 (0.70)	0.2936	2.11 (0.89)	0.0181	0.01 (1.83)	0.9955
T. Experience*time	-0.10 (0.04)	0.008	-0.03 (0.04)	0.4245	-0.05 (0.05)	0.3182	-0.15 (0.11)	0.1739

Table 15: *Parameter estimates (with standard errors in braces) of the non-proportional odds model with Outside_of_school as the dependent variable. Parameter estimates of logits $P(Y \leq 2)$, $P(Y \leq 3)$ and $P(Y \leq 4)$ were obtained via the Firth's method. For this research, only parameters of Logit $P(Y \leq 2)$ should be interpreted but the standard errors are not to be trusted since correlation was not accounted for.*

Parameter	P(Y=1)		P(Y≤2)		P(Y≤3)		P(Y≤4)	
	Estimate	P-value	Estimate	P-value	Estimate	P-value	Estimate	P-value
Intercept	0.64 (0.81)	0.4308	2.16 (1.57)	0.1696	0.85 (1.68)	0.611	2.38 (2.01)	0.2359
Function	-0.79 (0.86)	0.3627	-4.65 (2.14)	0.0299	-2.79 (2.26)	0.2158	-0.46 (2.80)	0.8681
T. Experience	-0.004 (0.02)	0.8384	0.02 (0.03)	0.5488	0.06 (0.04)	0.0945	0.032 (0.05)	0.5177
Time	0.00 (0.41)	1.000	4.00E-15 (0.93)	1.000	0.55 (1.07)	0.6078	-7.22E-15 (1.15)	1.000
Function*Time	0.22 (0.52)	0.6782	3.45 (1.72)	0.0452	2.31 (1.82)	0.2023	1.12 (1.97)	0.571

Table 16: *Parameter estimates (with standard errors in braces) of the non-proportional odds model with Parents_pressure as the dependent variable. Parameter estimates of logit $P(Y \leq 4)$ were obtained via the Firth's method. For this research, only parameters of Logit $P(Y \leq 2)$ should be interpreted.*

Parameter	P(Y=1)		P(Y≤2)		P(Y≤3)		P(Y≤4)	
	Estimate	P-value	Estimate	P-value	Estimate	P-value	Estimate	P-value
Intercept	2.39 (1.83)	0.1934	3.60 (1.84)	0.0506	2.05 (1.50)	0.1729	-0.59 (3.45)	0.8632
Function	-0.05 (1.10)	0.9647	-0.68 (1.11)	0.5382	-1.10 (1.03)	0.2838	0.85 (2.12)	0.6868
Oudenaarde	-0.16 (1.47)	0.9159	0.21 (1.24)	0.867	-0.67 (1.16)	0.566	0.76 (2.84)	0.7876
Vlaamse Ardennen	-4.08 (2.14)	0.0567	-0.86 (1.84)	0.6376	-0.28 (1.56)	0.858	0.01 (2.99)	0.9973
Antwerpen	-3.53 (1.59)	0.0265	-2.53 (1.41)	0.0733	-1.75 (1.67)	0.2959	0.68 (3.01)	0.8214
Time	-2.99 (1.52)	0.0492	-3.15 (1.29)	0.0146	-1.30 (0.96)	0.1759	1.81 (2.54)	0.4776
T. Experience	-0.05 (0.05)	0.3683	-0.10 (0.06)	0.1095	-0.03 (0.05)	0.4809	0.08 (0.12)	0.506
T. Experience*Time	0.06 (0.04)	0.1335	0.09 (0.04)	0.0272	0.05 (0.03)	0.1451	-0.04 (0.09)	0.6488
Function*Time	-0.18 (0.75)	0.8153	0.33 (0.73)	0.6521	0.50 (0.68)	0.4581	-0.22 (1.52)	0.8834
Oudenaarde*Time	0.044 (1.13)	0.9689	0.46 (0.79)	0.5589	1.19 (0.73)	0.1042	-0.12 (2.03)	0.9541
Vlaamse Ardennen*Time	2.74 (1.45)	0.0585	0.87 (1.24)	0.4887	0.40 (1.02)	0.6974	-0.14 (2.17)	0.9503
Antwerpen*Time	2.70 (1.13)	0.0165	2.98 (0.97)	0.0021	2.29 (1.21)	0.0575	-0.31 (2.16)	0.8868

Table 17: *Parameter estimates (with standard errors in braces) of the non-proportional odds model with Colleagues_not_open as the dependent variable. For this research, only parameters of Logit $P(Y \leq 2)$ should be interpreted.*

	P(Y=1)		P(Y≤2)		P(Y≤3)		P(Y≤4)	
Parameter	Estimate	P-value	Estimate	P-value	Estimate	P-value	Estimate	P-value
Intercept	1.84 (0.86)	0.0312	1.33 (0.81)	0.0981	1.43 (0.89)	0.107	2.77 (1.64)	0.0924
Function	1.22 (1.38)	0.374	0.84 (0.93)	0.3655	0.08 (1.01)	0.9347	-1.20 (1.69)	0.4787
T. Experience	-0.02 (0.03)	0.3534	0.01 (0.02)	0.5286	0.02 (0.02)	0.3227	0.02 (0.04)	0.5745
Time	-1.69 (0.50)	0.0007	-0.88 (0.44)	0.0457	-0.80 (0.49)	0.1037	-0.44 (0.76)	0.5648
Function*Time	-1.66 (1.19)	0.1605	-0.91 (0.57)	0.113	-0.18 (0.61)	0.7723	0.64 (0.98)	0.5104

Table 18: *Parameter estimates (with standard errors in braces) of the non-proportional odds model with Resources_weaker_children as the dependent variable. Parameter estimates for logit $P(Y \leq 4)$ were obtained via the Firth's method. For this research, only parameters of logit $P(Y \leq 2)$ should be interpreted.*

	P(Y=1)		P(Y≤2)		P(Y≤3)		P(Y≤4)	
Parameter	Estimate	P-value	Estimate	P-value	Estimate	P-value	Estimate	P-value
Intercept	-1.40 (0.84)	0.0959	1.30 (0.87)	0.1321	1.79 (1.30)	0.1674	3.88 (2.96)	0.1902
Function	1.85 (1.00)	0.0652	0.30 (1.04)	0.772	-1.11 (1.40)	0.4284	-2.62 (3.56)	0.4611
T. Experience	0.002 (0.02)	0.9068	0.01 (0.02)	0.6994	0.004 (0.03)	0.9085	0.08 (0.06)	0.1848
Time	0.53 (0.49)	0.2821	-0.31 (0.48)	0.5262	0.44 (0.76)	0.5648	-1.14 (1.60)	0.4765
Function*Time	-1.59 (0.64)	0.0133	-0.41 (0.63)	0.5103	0.47 (0.94)	0.6144	2.26 (2.26)	0.3169

Table 19: *Parameter estimates (with standard errors in braces) of the non-proportional odds model with Long_term_effect as the dependent variable. Parameter estimates for logits $P(Y \leq 3)$ and $P(Y \leq 4)$ were obtained via the Firth's method. For this research, only parameters of logit $P(Y \leq 2)$ should be interpreted.*

	P(Y=1)		P(Y≤2)		P(Y≤3)		P(Y≤4)	
Parameter	Estimate	P-value	Estimate	P-value	Estimate	P-value	Estimate	P-value
Intercept	2.42 (1.01)	0.016	6.26 (2.01)	0.0019	9.17 (3.73)	0.014	5.29 (3.30)	0.1094
Function	-1.11 (1.08)	0.3051	-0.91 (2.51)	0.7172	2.28 (3.55)	0.521	2.34 (3.68)	0.5257
T. Experience	-0.004 (0.02)	0.813	-0.05 (0.03)	0.0947	-0.23 (0.11)	0.0287	-0.14 (0.09)	0.1177
Time	-1.20 (0.58)	0.037	-1.76 (1.16)	0.1283	4.08E-15 (1.24)	1.000	1.16 (1.62)	0.4739
Function*Time	0.25 (0.67)	0.7131	0.58 (1.38)	0.6774	-1.19 (2.07)	0.5661	-1.16 (2.48)	0.6399

Table 20: *Parameter estimates and standard errors of the proportional odds model with Vain as the dependent variable.*

Parameter	Estimate	Std. Error	P-value
Intercept1 [P(Y=1)]	-2.34	0.93	0.0123
Intercept2 [P(Y≤2)]	0.25	0.90	0.7823
Intercept3 [P(Y≤3)]	1.22	0.92	0.1862
Function	0.65	1.01	0.5219
T. Experience	-0.02	0.02	0.3379
Time	1.10	0.54	0.0405
Function*Time	-0.85	0.64	0.1796

Table 21: *Parameter estimates (with standard errors in braces) of the non-proportional odds model with Not_feasible_differentiation as the dependent variable. Parameter estimates for logit $P(Y≤4)$ were obtained via the Firth's method. For this research, only parameters of logit $P(Y≤2)$ should be interpreted.*

Parameter	P(Y=1)		P(Y≤2)		P(Y≤3)		P(Y≤4)	
	Estimate	P-value	Estimate	P-value	Estimate	P-value	Estimate	P-value
Intercept	-2.28 (1.06)	0.031	-1.54 (0.84)	0.0677	-2.59 (1.30)	0.0473	-2.15 (1.10)	0.0518
Function	-2.63 (1.67)	0.1161	0.74 (0.93)	0.4282	0.38 (1.26)	0.7646	-2.36 (1.68)	0.1609
time	0.89 (0.59)	0.131	1.70 (0.49)	0.0005	3.04 (0.99)	0.0024	0.84 (0.60)	0.166
Experience_teaching	-0.02 (0.02)	0.4508	-0.02 (0.02)	0.3694	-0.001 (0.02)	0.9568	-0.02 (0.02)	0.4787
time*Function	0.99 (0.89)	0.2634	-0.97 (0.60)	0.1078	-1.03 (1.08)	0.3405	0.87 (0.95)	0.3588

Table 22: *Parameter estimates (with standard errors in braces) of the non-proportional odds model with Extra_time_differentiation as the dependent variable. Parameter estimates for logit $P(Y≤4)$ were obtained via the Firth's method. For this research, only parameters of logit $P(Y≤2)$ should be interpreted.*

Parameter	P(Y=1)		P(Y≤2)		P(Y≤3)		P(Y≤4)	
	Estimate	P-value	Estimate	P-value	Estimate	P-value	Estimate	P-value
Intercept	-0.78 (1.17)	0.5055	-0.02 (0.81)	0.979	0.76 (0.85)	0.3692	1.44 (2.26)	0.5243
Function	-1.96 (2.01)	0.3297	-0.45 (0.99)	0.6487	-2.14 (0.93)	0.0207	0.35 (2.38)	0.8832
T. Experience	-0.04 (0.04)	0.329	0.004 (0.02)	0.8458	-0.01 (0.02)	0.5968	0.03 (0.03)	0.4258
Time	-0.26 (0.69)	0.7048	0.12 (0.44)	0.7814	0.14 (0.46)	0.7629	1.13 (1.65)	0.4933
Function*Time	0.26 (1.25)	0.8342	-0.82 (0.64)	0.2023	0.74 (0.56)	0.1862	-1.29 (1.74)	0.459

Table 23: *Parameter estimates (with standard errors in braces) of the non-proportional odds model with Less_time_differentiation as the dependent variable. For this research, only parameters of logit $P(Y \leq 2)$ should be interpreted.*

Parameter	P(Y=1)		P(Y≤2)		P(Y≤3)		P(Y≤4)	
	Estimate	P-value	Estimate	P-value	Estimate	P-value	Estimate	P-value
Intercept	-1.46 (1.48)	0.3243	-0.01 (0.73)	0.9879	0.67 (0.81)	0.4116	2.17 (1.60)	0.1756
Function	-1.51 (1.51)	0.3148	0.74 (0.81)	0.3586	-0.44 (0.89)	0.6247	1.81 (1.80)	0.3155
T. Experience	0.04 (0.04)	0.2908	0.01 (0.02)	0.8575	-0.01 (0.02)	0.7724	-0.02 (0.05)	0.775
Time	-0.81 (0.82)	0.3219	0.000 (0.34)	1.000	0.14 (0.42)	0.7386	0.44 (0.76)	0.5652
Function*Time	0.81 (0.98)	0.4095	-0.58 (0.48)	0.2286	0.09 (0.54)	0.8728	-0.86 (1.06)	0.4162

Table 24: *Parameter estimates (with standard errors in braces) of the non-proportional odds model with Ache_for_differentiation as the dependent variable. For this research, only parameters of logit $P(Y \leq 2)$ should be interpreted.*

Parameter	P(Y=1)		P(Y≤2)		P(Y≤3)		P(Y≤4)	
	Estimate	P-value	Estimate	P-value	Estimate	P-value	Estimate	P-value
Intercept	-1.74 (1.31)	0.1862	0.86 (1.33)	0.5179	1.20 (1.32)	0.3655	0.26 (4.43)	0.9534
Function	1.85 (0.97)	0.0554	-1.55 (1.20)	0.1949	-2.05 (1.20)	0.0877	1.02 (2.94)	0.7288
T. Experience	0.05 (0.06)	0.3798	0.15 (0.07)	0.0213	0.12 (0.07)	0.0819	0.20 (0.23)	0.3935
Time	0.27 (0.90)	0.7668	-0.20 (0.76)	0.7952	-0.30 (0.72)	0.6781	1.68 (2.69)	0.5312
Function*Time	-1.56 (0.66)	0.0166	0.71 (0.70)	0.31	1.1147 (0.67)	0.10	-0.97 (1.84)	0.5963
T. Experience*time	-0.02 (0.04)	0.6261	-0.09 (0.04)	0.0131	-0.06 (0.04)	0.1015	-0.10 (0.13)	0.4058

Table 25: *Parameter estimates (with standard errors in braces) of the non-proportional odds model with Selfesteem_pullout as the dependent variable. Parameter estimates for logits $P(Y \leq 3)$ and $P(Y \leq 4)$ were obtained via the Firth's method. For this research, only parameters of logit $P(Y \leq 2)$ should be interpreted.*

Parameter	P(Y=1)		P(Y≤2)		P(Y≤3)		P(Y≤4)	
	Estimate	P-value	Estimate	P-value	Estimate	P-value	Estimate	P-value
Intercept	-0.13 (0.91)	0.8907	1.60 (0.96)	0.0962	0.23 (2.02)	0.9104	7.41 (3.89)	0.0565
Function	-0.76 (1.13)	0.4995	1.73 (1.15)	0.133	0.27 (2.14)	0.9014	1.18 (4.20)	0.7793
Experience_teaching	0.01 (0.02)	0.7935	-0.01 (0.02)	0.6973	0.03 (0.03)	0.3044	-0.14 (0.08)	0.1044
time	-0.40 (0.55)	0.4663	-0.31 (0.53)	0.5632	1.67 (1.57)	0.2859	7.02E-15 (1.98)	1.000
Function*Time	-0.09 (0.74)	0.9029	-1.36 (0.70)	0.0496	-0.9549 (1.68)	0.57	-1.14 (2.52)	0.6524

7.1.2 Model Results for dependent variables in the specific knowledge section

Table 26: *Parameter estimates of the non-proportional odds model with Not_to_have_differentiation as the dependent variable. For this research, only parameters of Logit $P(Y=1)$ should be interpreted.*

Parameter	P(Y=1)			P(Y≤2)		
	Estimate	Std. error	P-value	Estimate	Std. error	P-value
Intercept	-3.60	1.25	0.004	-2.77	1.20	0.0213
Function	0.17	0.88	0.8506	-1.01	1.07	0.3487
T. Experience	0.14	0.05	0.0036	0.12	0.06	0.0374
Oudenaarde	1.08	0.52	0.0377	0.87	0.52	0.0906
Vlaamse Ardennen	1.42	0.57	0.0136	1.19	0.67	0.0749
Antwerpen	1.25	0.61	0.0394	0.96	0.63	0.1271
Time	1.41	0.71	0.049	1.35	0.70	0.0558
Function*Time	0.80	0.52	0.1214	1.98	0.76	0.0094
T. Experience*time	-0.09	0.03	0.0033	-0.07	0.04	0.0398

Table 27: *Parameter estimates of the proportional odds model with Choose_differentiation as the dependent variable*

Parameter	Estimate	Std. error	P-value
Intercept1 [P(Y=1)]	-1.83	0.72	0.011
Intercept2 [P(Y≤ 2)]	-1.33	0.72	0.0641
Function	3.34	0.95	0.0005
Time	0.98	0.44	0.0242
Function*Time	-1.23	0.57	0.032

Table 28: *Parameter estimates of the non-proportional odds model with Eliminate_differentiation as the dependent variable. For this research, only parameters of Logit $P(Y=3)$ should be interpreted.*

Parameter	P(Y=3)			P(Y≥2)		
	Estimate	Std. Error	P-value	Estimate	Std. Error	P-value
Intercept	-1.10	0.73	0.1326	-1.60	0.74	0.0294
Function	2.17	1.05	0.0381	1.83	1.14	0.1076
Time	1.04	0.47	0.0276	1.66	0.52	0.0013
Function*Time	-0.66	0.68	0.3323	-0.32	0.84	0.6999

Table 29: *Parameter estimates of the proportional odds model with Mandatory_differentiation as the dependent variable*

Parameter	Estimate	Std. Error	P-value
Intercept3 [P(Y=3)]	-3.74	0.96	0.0001
Intercept2 [P(Y≥2)]	-3.11	0.93	0.0009
Function	-0.39	0.94	0.6742
Oudenaarde	1.09	0.50	0.0294
Vlaamse Ardennen	1.62	0.73	0.0262
Antwerpen	0.56	0.56	0.3175
T. Experience	-0.03	0.02	0.109
Time	2.49	0.46	<.0001
Function*Time	0.32	0.62	0.6114

Table 30: *Parameter estimates of the non-proportional odds model with Many_mistakes_diff_continue as the dependent variable. Parameter estimates of Logit P(Y=5) and Logit p(Y≥2) were obtained via the Firth's method. For this research, only parameters of Logit p(Y≥4) should be interpreted.*

Parameter	P(Y=5)		P(y≥4)		P(Y≥3)		P(Y≥2)	
	Estimate	P-value	Estimate	P-value	Estimate	P-value	Estimate	P-value
Intercept	-3.27 (3.19)	0.3041	1.58 (0.88)	0.0725	0.14 (0.88)	0.8761	2.09 (1.19)	0.0788
Function	-2.95 (4.17)	0.4795	-1.77 (0.97)	0.0689	-1.80 (1.03)	0.0795	-2.00 (1.93)	0.2996
T. Experience	-0.05 (0.05)	0.3566	-0.02 (0.02)	0.306	-0.03 (0.02)	0.1578	-0.04 (0.03)	0.1501
Time	2.37E-14 (1.95)	1.00	-1.26 (0.53)	0.0174	0.37 (0.51)	0.4659	0.21 (0.65)	0.7521
Function*Time	2.27 (2.44)	0.3519	1.70 (0.64)	0.0078	1.77 (0.70)	0.0112	2.48 (1.61)	0.1242

Table 31: *Parameter estimates of the non-proportional odds model with Working_attitude_diff_continu as the dependent variable. Parameter estimates of Logit P(Y=5) and Logit p(Y≥2) were obtained via the Firth's method. For this research, only parameters of Logit p(Y≥4) should be interpreted.*

Parameter	P(Y=5)		P(P≥4)		P(Y≥3)		P(Y≥2)	
	Estimate	P-value	Estimate	P-value	Estimate	P-value	Estimate	P-value
Intercept	-3.79 (3.43)	0.2699	0.24 (1.07)	0.8244	-0.59 (1.01)	0.56	2.64 (1.44)	0.0666
Function	-3.22 (4.27)	0.4512	-0.08 (1.12)	0.949	-1.11 (1.02)	0.2755	-3.52 (1.98)	0.0753
Oudenaarde	-1.70 (1.62)	0.2934	0.24 (0.39)	0.5398	0.31 (0.50)	0.5374	-0.41 (0.67)	0.5456
Vlaamse Ardennen	-0.65 (1.69)	0.7002	1.12 (0.50)	0.026	1.21 (0.64)	0.0584	0.19 (0.89)	0.8283
Antwerpen	1.9 (1.04)	0.0685	0.87 (0.49)	0.0744	0.53 (0.55)	0.3362	0.69 (0.89)	0.4369
T. Experience	-0.09 (0.06)	0.0881	-0.02 (0.02)	0.2303	-0.02 (0.02)	0.3207	0.01 (0.03)	0.6335
Time	-0.001 (2.07)	0.9997	-0.69 (0.63)	0.2755	0.16 (0.54)	0.7699	-0.87 (0.69)	0.2098
Function*Time	3.12 (2.53)	0.2176	0.56 (0.73)	0.4394	1.65 (0.68)	0.0152	3.54 (1.58)	0.0248

Table 32: *Parameter estimates of the non-proportional odds model with Opinion_child_accell as the dependent variable. For this research, only parameters of Logit $P(Y=1)$ should be interpreted.*

Parameter	P(Y=1)			P(Y≤2)		
	Estimate	Std. Error	P-value	Estimate	Std. Error	P-value
Intercept	-2.03	1.56	0.1943	-3.13	1.43	0.029
Function	-2.03	1.45	0.1633	-0.19	1.31	0.8849
T. Experience	0.09	0.07	0.2315	0.08	0.07	0.2038
Time	2.35	0.93	0.0117	2.75	0.90	0.0023
Function*Time	-0.93	0.72	0.1946	-1.20	0.70	0.0836
T. Experience*time	-0.11	0.04	0.0162	-0.06	0.04	0.1128
T. Experience*Function	0.13	0.04	0.0005	0.05	0.04	0.1821

Table 33: *Parameter estimates of the non-proportional odds model with Catch_up_accell as the dependent variable. Parameter estimates for Logit $P(Y=1)$ were obtained via the Firth's method. For this research, only parameters of Logit $P(Y=1)$ should be interpreted.*

Parameter	P(Y=1)			P(Y≤2)		
	Estimate	Standard	P-value	Estimate	Standard	P-value
Intercept	-7.45	2.93	0.0109	-0.63	1.07	0.5594
Function	8.04	2.99	0.0072	-0.02	1.20	0.9864
T. Experience	-0.03	0.02	0.1115	-0.03	0.02	0.1314
Time	4.08	1.49	0.0061	1.22	0.62	0.0485
Function*Time	-3.92	1.55	0.0112	0.29	0.78	0.7155

Table 34: *Parameter estimates of the proportional odds model with Extra_basic_differentiation as the dependent variable.*

Parameter	Estimate	Std. Error	P-value
Intercept1 [P(Y=1)]	-7.16	1.29	<.0001
Intercept2 [P(Y≤2)]	-6.48	1.29	<.0001
Function	6.58	1.46	<.0001
T. Experience	0.03	0.02	0.1129
Time	3.48	0.68	<.0001
Function*Time	-2.30	0.89	0.0095

7.2 Barplots of dependent variables at pre and post-training

7.2.1 Opinion and concerns

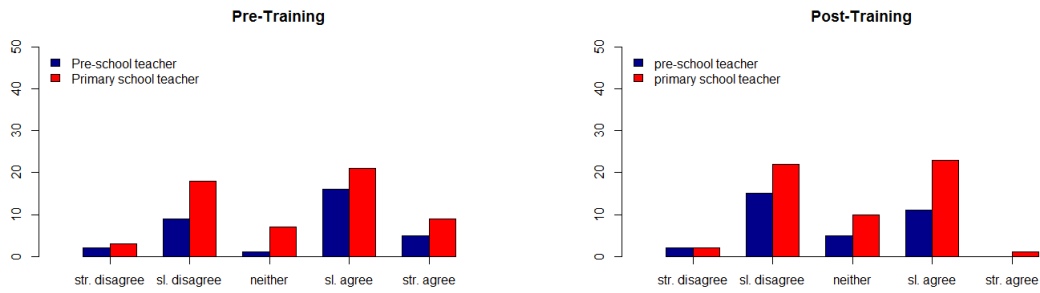


Figure 6: *Difficult_to_detect*

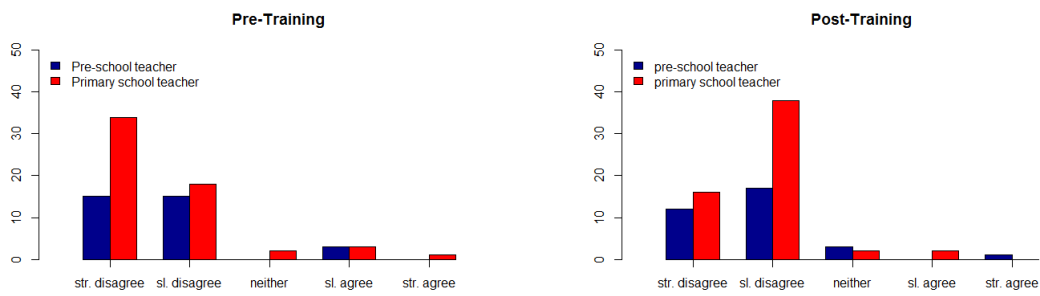


Figure 7: *Overburdened*

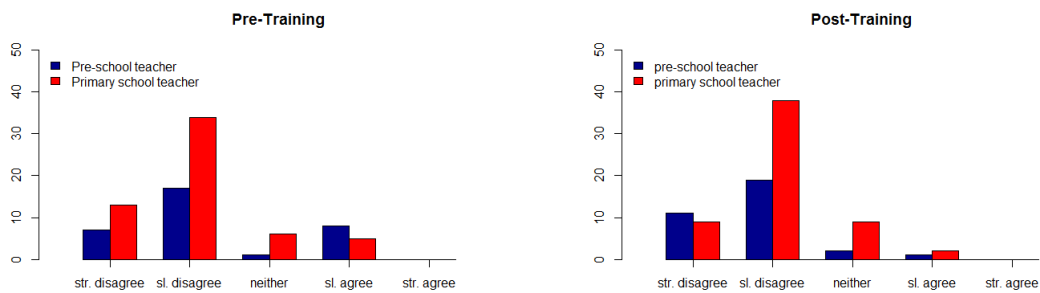


Figure 8: *Fear_of_failure*

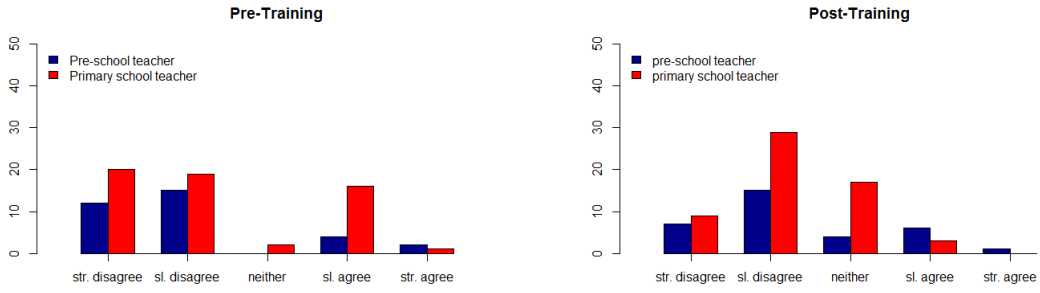


Figure 9: *Being_a_child*

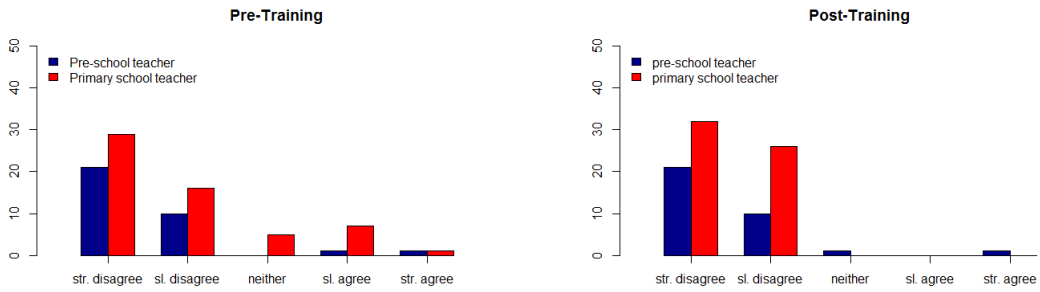


Figure 10: *Outside_of_school*

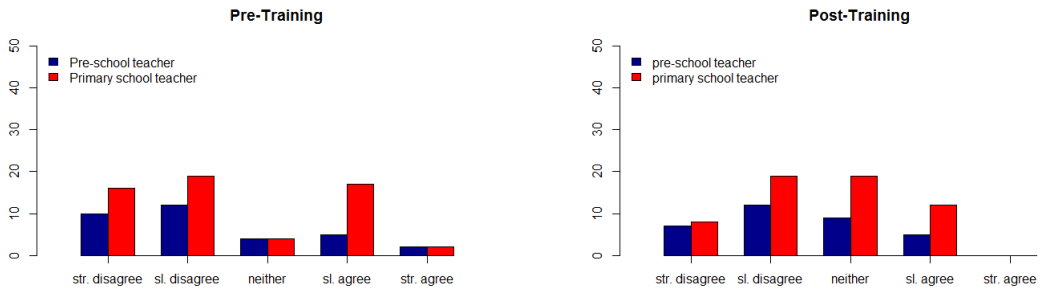


Figure 11: *Parents_pressure*

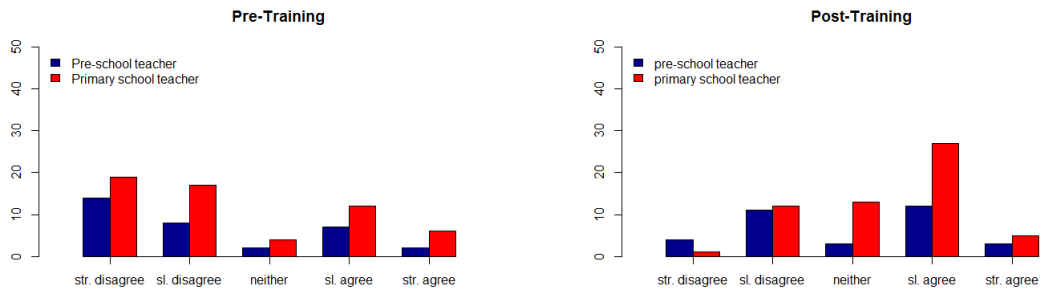


Figure 12: *Colleagues_not_open*

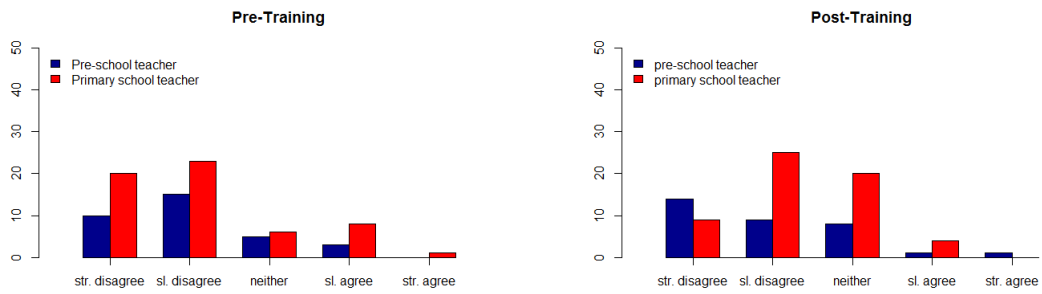


Figure 13: *Resources_weaker_children*

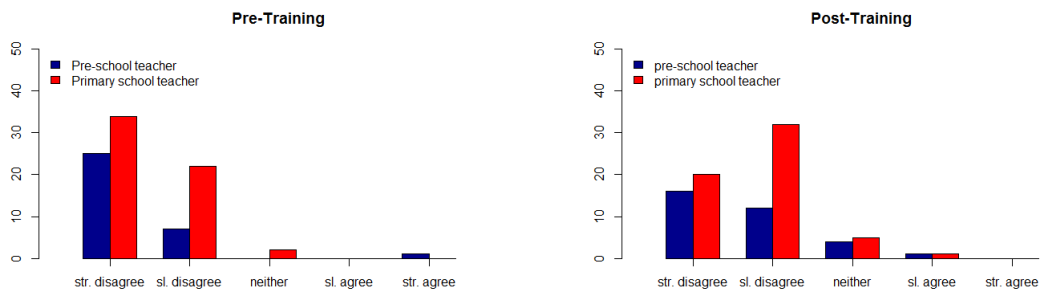


Figure 14: *Long_term_effect*

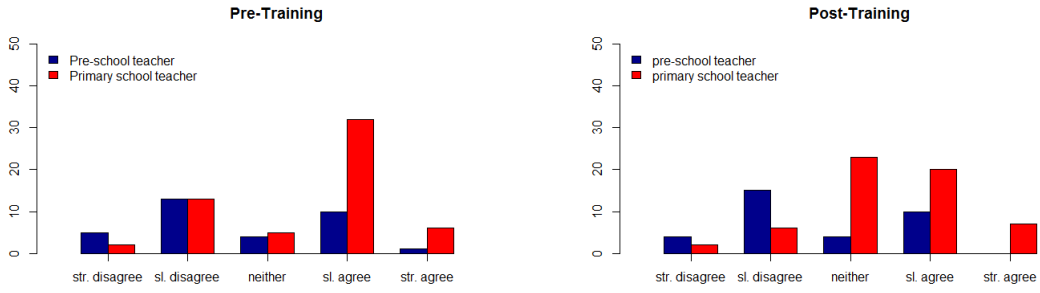


Figure 15: *Extra_time_differentiation*

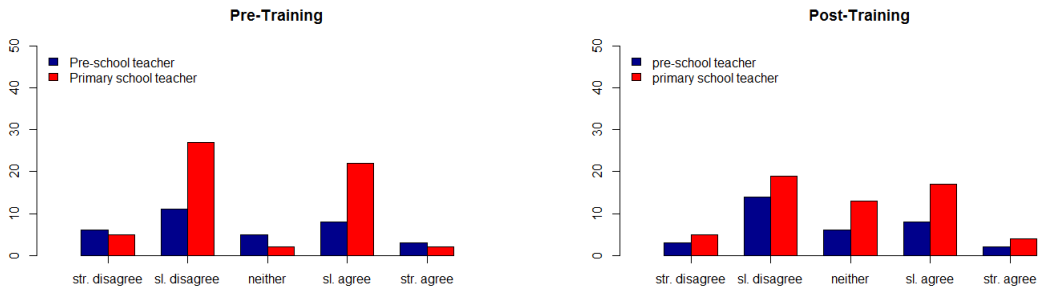


Figure 16: *Less_time_differentiation*

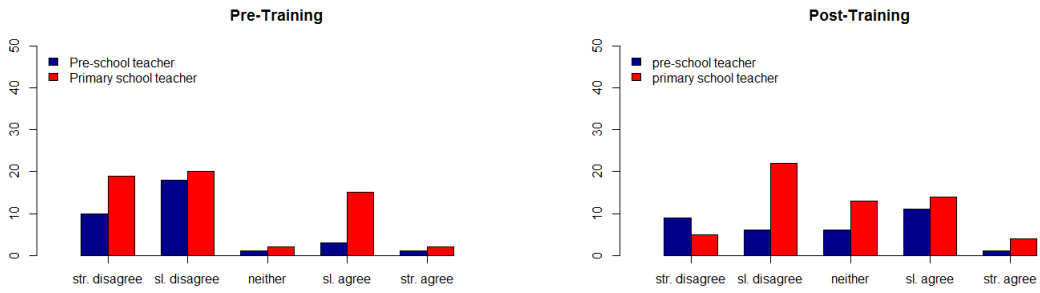


Figure 17: *Ache_for_differentiation*

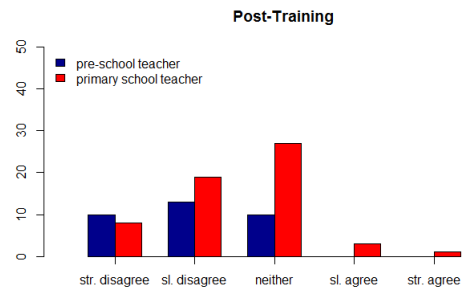
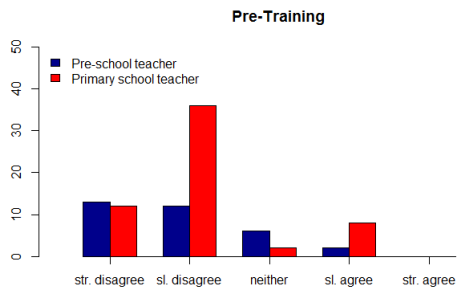


Figure 18: *Selfesteem_pullout*

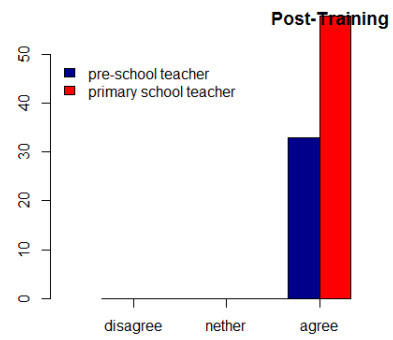
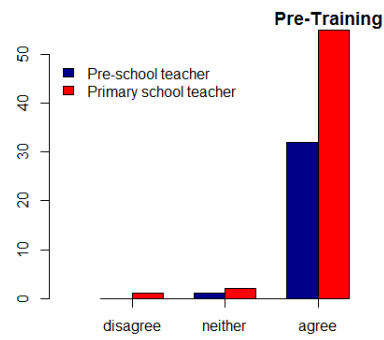


Figure 19: *Convinced_benefit*

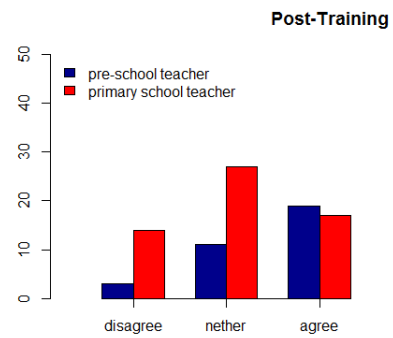
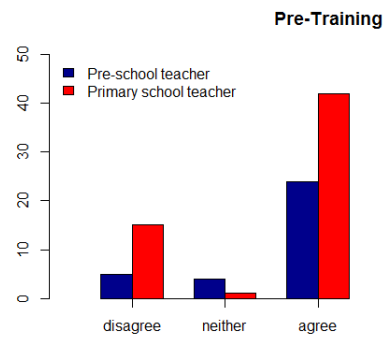


Figure 20: *Accelleration*

7.2.2 Specific Knowledge

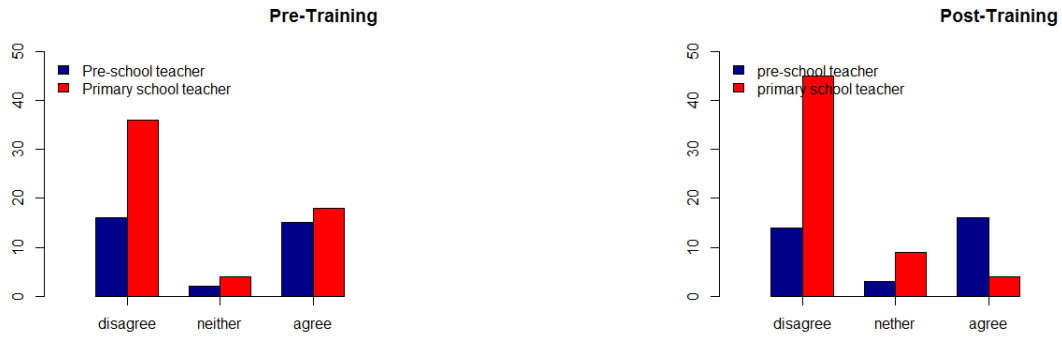


Figure 21: *Nice_to_have_differentiation*

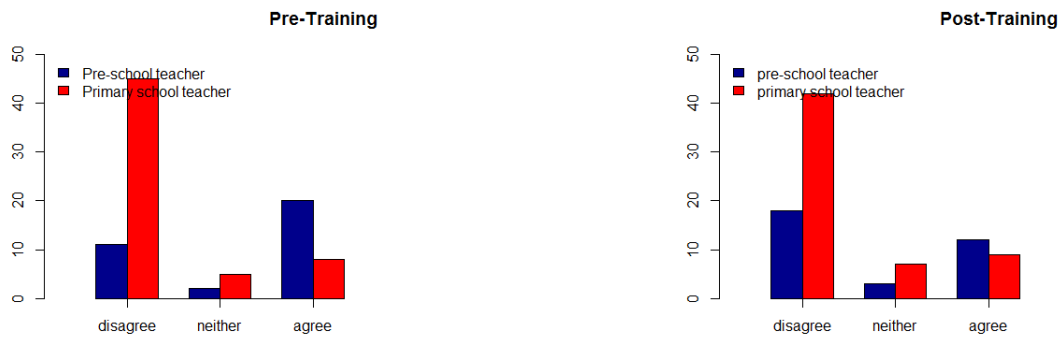


Figure 22: *Choose_differentiation*

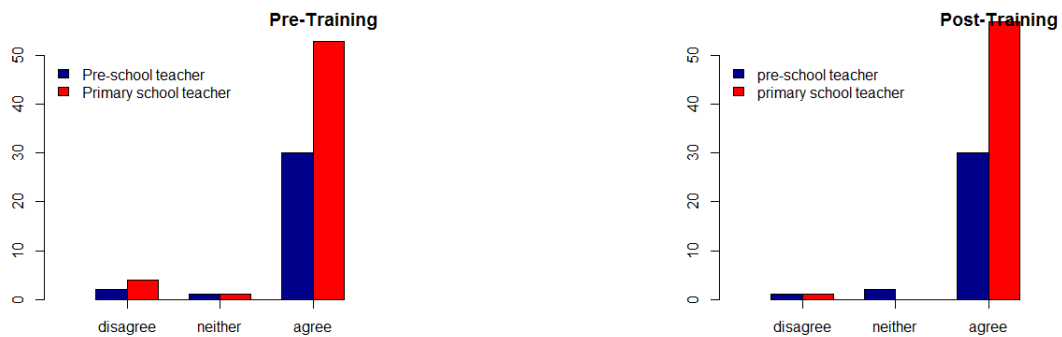


Figure 23: *Challenging_differentiation*

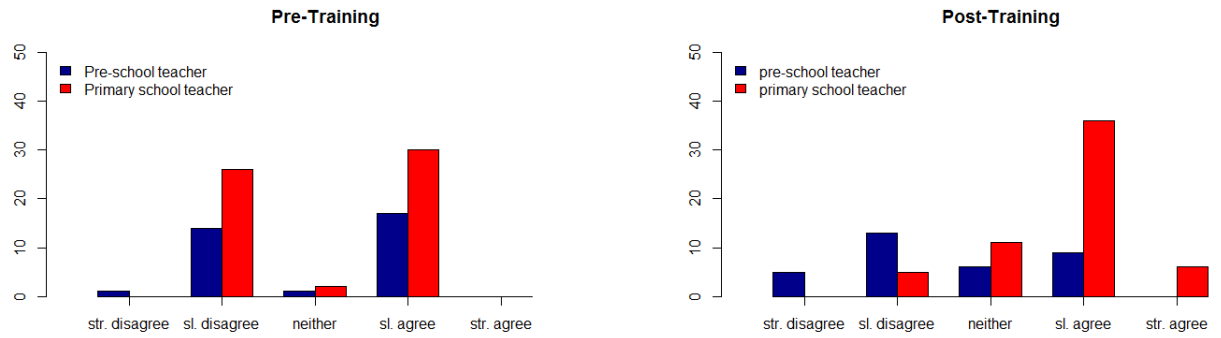


Figure 24: *Not_want_diff_continu*

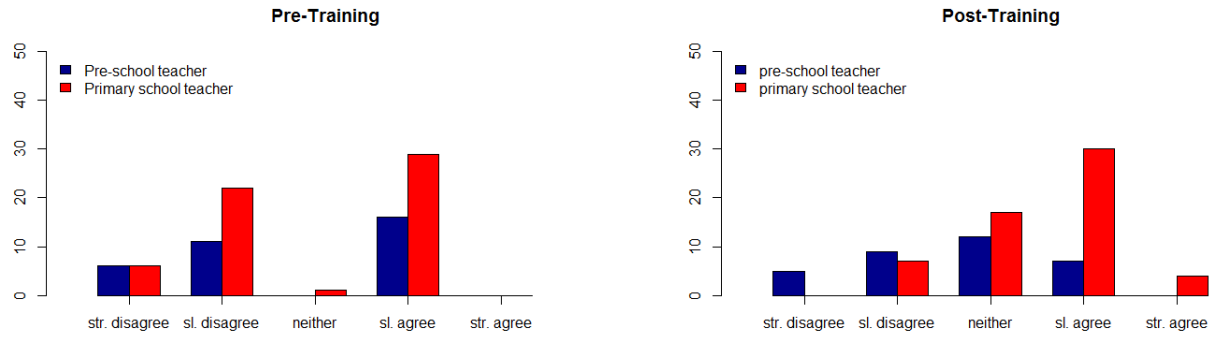


Figure 25: *Many_mistakes_diff_continue*

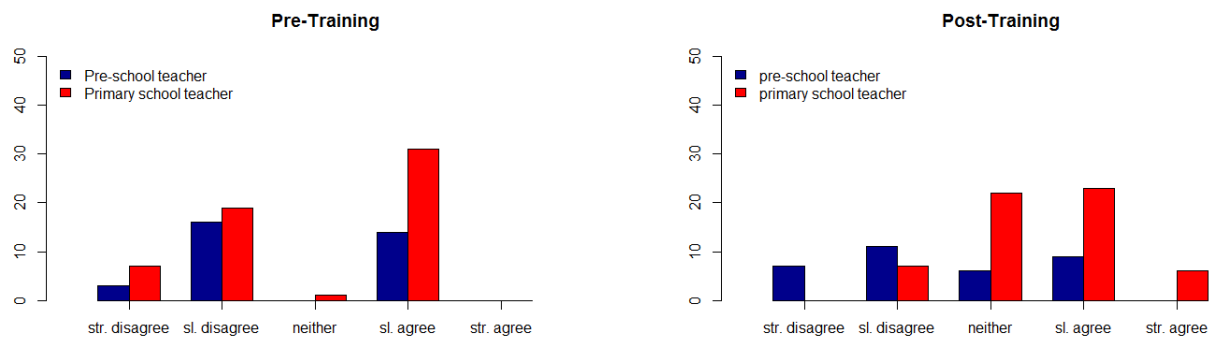


Figure 26: *Working_attitude_diff_continue*

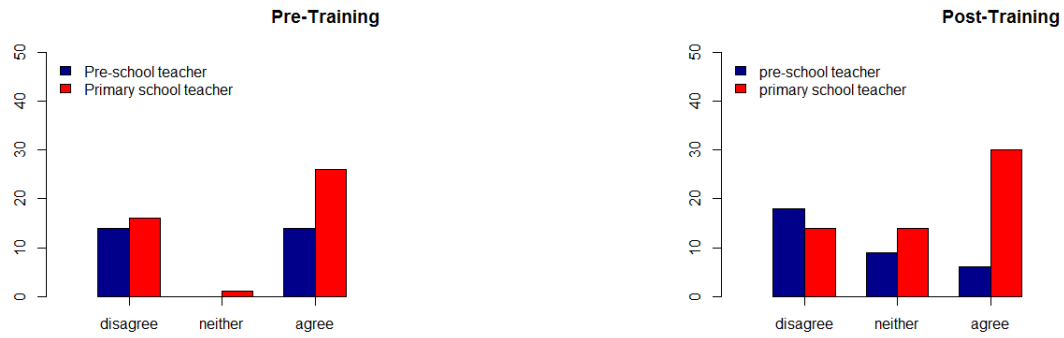


Figure 27: *Opinion_child_accell*

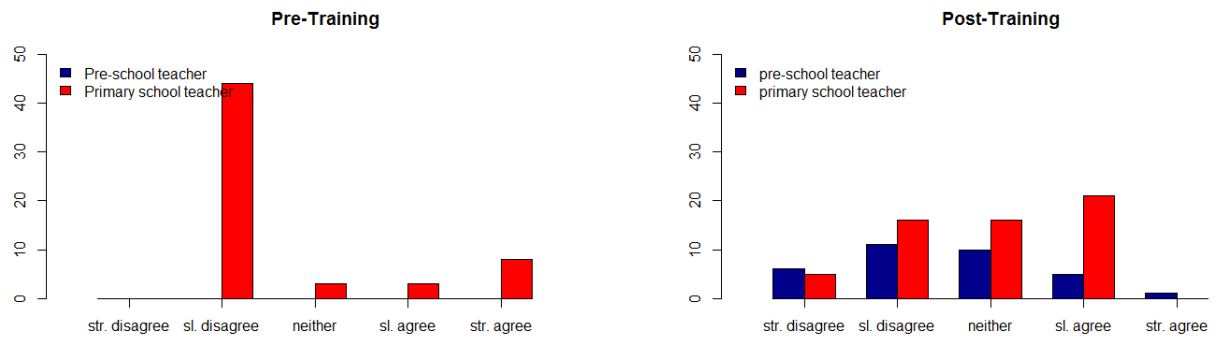


Figure 28: *gap_accell*

7.3 Example of R codes of Barplots

```
\subsection{Example of R codes of Barplots}

\begin{verbatim}

#### BAR PLOTS #####
baselinereal <- read.delim("C:/Users
/Gilles/Desktop/Thesis Gilles/baselinereal.txt", header=TRUE, na.strings="")
View(baselinereal)
evolutionreal<- read.delim("C:/Users
/Gilles/Desktop/Thesis Gilles/evolutionreal.txt", header=TRUE, na.strings="")
View(evolutionreal)
#####
KNOWLEDGE
#par( mfrow = c( 1, 2 ), oma = c( 0, 0, 2, 0 ) )
##### PRE MEASUREMENT #####
windows()
oknowledge=ordered(baselinereal$Knowledge, levels=c("not", "to a lesser extend",
"to a large extend"))
counts <- table(baselinereal$Function, oknowledge)  barplot(counts,
main="Pre-Training",width=0.18,
xlim = c(0,2), ylim=c(0,50), col=c("darkblue","red"),
legend = rownames(counts), beside=TRUE,
args.legend = list(x="topleft", bty="n"), axis.lty=1,
names.arg =c("not", "to a lesser extent",
"to a large extent"))

##### POST MEASUREMENT #####

windows()
oknowledge=ordered(evolutionreal$Knowledge, levels=c("to a lesser extend",
"to a large extend"))
counts <- table(evolutionreal$Function, oknowledge)  barplot(counts,
main="Post-training",width=0.18,
xlim = c(0,2), ylim=c(0,50), col=c("darkblue","red"),
legend = rownames(counts), args.legend =
list(x="topleft", bty="n"), beside=TRUE, axis.lty=1,
names.arg =c("to a lesser extent", "to a large extent"))
#####
```

7.4 Example of SAS codes for proportional odds model and the Non-proportional odds model and checking the proportional odds assumption

7.4.1 SAS codes for Proportional Odds Model and Checking of proportional odds assumption

```
/******EXPERIENCE *****/
proc genmod data=final descending ;
class tid timeclass Function School_community/ param=ref ref=first;
model experience = Function Experience_teaching time Function*time /aggregate
dist=multinomial TYPE3 link=cumlogit;
repeated subject=tid / type=ind covb corrw within=timeclass modelse;
run;
```

```
/* CHECKING PROPORTIONAL ODDS*/
proc logistic data=final descending;
class tid timeclass Function School_community / param=ref ref=first;
model experience = Function Experience_teaching time Function*time/
link=logit aggregate scale=none;run;
```

7.4.2 SAS Codes For Non-Proportional Odds Model and Checking of Proportional Odds Assumption

```
/****** ACCELERATION *****/
proc genmod data=final descending;
class tid timeclass Function School_community/ param=ref ref=first;
model Accelleration = Function School_community Experience_teaching time
Function*time School_community*time Experience_teaching*time /aggregate
dist=multinomial TYPE3 link=cumlogit;
repeated subject=tid / type=ind covb corrw within=timeclass modelse;run;
```

```
/* CHECKING PROPORTIONAL ODDS ASSUMPTION */
proc logistic data=final descending;
class tid timeclass Function School_community / param=ref ref=first;
model Accelleration = Function School_community Experience_teaching time
Function*time School_community*time Experience_teaching*time / link=logit
```

```

aggregate scale=none;run;

data logit1;set final;
if Accelleration=2 then Accelleration=0;
if Accelleration=3 then Accelleration=0;
if Accelleration=4 then Accelleration=1;run;

data logit2;set final;
if Accelleration=2 then Accelleration=0;
if Accelleration=3 then Accelleration=1;
if Accelleration=4 then Accelleration=1;run;

proc freq data=logit2;tables  Accelleration;run;

PROC freq DATA=final;tables  Accelleration;run;

/* NON-PROPORTIONAL ODD MODELS */
/* LOGIT 1 */
proc genmod data=logit1 descend;
class tid timeclass Function(ref="1") School_community (ref="1")/ param=ref;
model Accelleration = Function School_community Experience_teaching
time Function*time School_community*time Experience_teaching*time /dist=bin;
repeated subject=tid / corr=ind corrw within=timeclass modelse;run;

/* LOGIT 2 */
proc genmod data=logit2 descend;
class tid timeclass Function(ref="1") School_community (ref="1")/ param=ref;
model Accelleration = Function School_community Experience_teaching
time Function*time School_community*time Experience_teaching*time /dist=bin;
repeated subject=tid / corr=ind corrw within=timeclass modelse;run;

```

...

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Research on the effectiveness of an in-depth training program for schools and parents, aimed at installing a challenging learning environment for gifted children in Belgian Schools

Richting: **Master of Statistics-Biostatistics**

Jaar: **2015**

in alle mogelijke mediaformaten, - bestaande en in de toekomst te ontwikkelen - , aan de Universiteit Hasselt.

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Ndungbogun, Gilles Ndanjo

Datum: **1/09/2015**