rijksuniversiteit groningen

faculteit gedrags- en maatschappijwetenschappen

Cognitive preconditions for learning of secondary special needs education pupils: profiles using cluster analysis

Student: C.M. van der Wal (S3745309)

c.m.van.der.wal.1@student.rug.nl

Thesis supervisor: M.J. Warrens

2nd assessor: L. Visscher

University of Groningen

Faculty of Behavioural and Social Sciences

Bachelor thesis Pedagogische Wetenschappen

May 25, 2022

6708 words

Samenvatting

Het academische leerproces van leerlingen wordt door meerdere factoren beïnvloed. Directe leervoorwaarden (bv. motivatie en taakgerichtheid) zijn voorbeelden van deze factoren. Het effect op leergedrag van individuele directe leervoorwaarden is onderzocht. Profielen van leerlingen van leervoorwaarden zijn niet eerder bestudeerd. Profielen op basis van clusteranalyse laten patronen zien in data die in eerste plaats niet zichtbaar waren, dit geeft meer inzicht in de mogelijkheden van leerlingen. De onderzoeksvraag was dan ook: welke profielen van directe leervoorwaarden kunnen geïdentificeerd worden voor leerlingen van het voortgezet speciaal onderwijs?

De data was verzameld over een periode van vijf jaar op zeven cluster-4 scholen voor voortgezet onderwijs in de drie provincies in Noord-Nederland. De steekproef bestond uit 1575 middelbare scholieren op het speciaal onderwijs. Voor de dataverzameling was de Leervoorwaardentest gebruikt. De clusteranalyse gaf modellen met 13 en 14 clusters aan als goed. Voor zowel het 13-cluster als het 14-clustermodel lieten de meeste clusters een patroon zien van ongeveer dezelfde score op alle directe leervoorwaarden. Dit liet zien dat leerlingen met een hoge score op motivatie waarschijnlijk ook een hoge score op de andere leervoorwaarden hebben. Op basis van de BIC is het 14-clustermodel gekozen als meest geschikte model. Een limitatie van het onderzoek was dat de steekproef alleen representatief was voor Noord-Nederland. Toekomstig onderzoek zou een steekproef uit heel Nederland kunnen onderzoeken. Een andere limitatie is dat maar één methode van clusteranalyse was gebruikt. Toekomstig onderzoek kan meerdere methoden gebruiken en vergelijken.

Introduction

Preconditions for learning, e.g. motivation and task orientation, are factors that influence an academic learning process, and thus academic achievement, either positively or negatively (Scholte & Van der Ploeg, 2011). In the context of education, to give suitable personal support to a pupil, it is important to know the possibilities and restrictions concerning the learning of the pupil (Radema & van Kessel, 2016). Pupils' learning can be influenced by pupils' cognitive ability, preconditions for learning, social-emotional development and more. Learning preconditions are factors that influence learning. There are two types of preconditions for learning. Cognitive preconditions are factors related to processing information, such as concentration and memory. Social-emotional preconditions are factors concerning the interaction between people and their emotions. This article will focus on cognitive preconditions for learning.

Examples of cognitive learning preconditions are motivation, task orientation, concentration, planning, work pace and perseverance (Scholte & Van der Ploeg, 2011). Motivation is the capacity of a pupil to commit to the work needed for school. Task orientation is the possibility of a pupil to complete tasks at school precisely and purposefully. Concentration means a pupil can focus his or her full attention on a task. Planning is the capacity of a pupil to think through tasks and complete them. Work pace is the possibility of a pupil to complete tasks quickly and effectively. Perseverance means a pupil is capable to keep working and even complete the most complicated task.

Prior research

Preconditions for learning are important factors for the academic learning process, and thus academic performance, of pupils. Within secondary education, the problems that are mentioned most frequently by teachers for pupils that need special care are lack of concentration, lack of motivation and low work pace (Smeets et al., 2019). Though initial academic results are strongly related to intelligence, growth in academic performance can also be strongly influenced by pupils' motivation and learning strategies used (Murayama et al., 2013). Pupils with higher motivation also show more engagement with learning (Lockl et al., 2021). Task-oriented pupils are more likely to link academic achievements to values such as effort, sacrifice and commitment. When pupils associate school success with values such as effort, this has a positive effect on pupils' intrinsic motivation to complete tasks, coping strategies development, enjoyment of effort, academic delight and better physical and psychological well-being (Usán Supervía & Salavera Bordás, 2020).

Planning and perseverance are important predictors of academic achievement. Planning contains, among others, inhibition and shifting. These elements along with planning are part of executive functions (Friedman et al., 2008; Larson et al., 2021). In this context the executive functions can be seen as related to the learning precondition planning. Whereas planning has not yet been thoroughly researched, executive functions have been found to be positively correlated with academic achievement (Best et al., 2011). The concept of grit can be seen as a combination of passion and perseverance towards a long term goal (Duckworth et al., 2007). Grit has been associated with having an effect on various aspects of a person's life, examples being academic achievement (Akos & Kretchmar, 2017) and psychological well-being (Datu et al., 2016). There is a significant difference between people with and without special needs for grit (Clark et al., 2020). This is true for pupils between the ages of 14 and 18. Pupils without an individualized education program (IEP) have higher grit than pupils with IEPs. When dividing grit into perseverance and interest, the same results presented for grit also hold for perseverance but do not hold for interest. The latter means that pupils with IEPs have lower perseverance than pupils without IEPs.

Secondary special needs education

In this study we will consider preconditions for learning for pupils in secondary special needs education. Pupils within special education can receive schooling until the year they turn 20 (Ministerie van Algemene Zaken, 2021). However, exceptions to this rule can be made. In the Netherlands, special needs education is divided into 4 clusters. The current study considers cluster 4 pupils, which are children with mental disorders or behavioural problems (Ministerie van Onderwijs Cultuur en Wetenschap, 2021). Along with a problematic attitude towards work another example of mental disorders and behavioural problems is autism spectrum disorder (ASD) (Manti et al., 2011). Pupils with ASD or a problematic attitude towards work are also present in general education because of the Appropriate Education Act (Dutch: Wet passend onderwijs) (Ministerie van Onderwijs Cultuur en Wetenschap, 2022). Within mainstream education two thirds of the pupils are reported to have a problematic attitude to work (van der Veen et al., 2010). Therefore, researching cluster 4 education could also give insight into pupils with special needs in general education.

Preconditions for learning have been researched extensively for pupils within special needs education. In America, pupils with and without the classification ‘special education’ have been studied on topics such as concentration, motivation and task orientation (Schaefer, 2004). Pupils with the classification ‘special education’ have, on average, more problems with tasks involving concentration, motivation or task orientation than pupils without the classification. Pupils with special educational needs are also more likely to leave school early (Wagner & Davis, 2006). Some researchers even found it to be twice as likely (Pijl et al., 2014). The most reported concerns of teachers regarding special needs pupils have been mapped out thoroughly. The most frequently mentioned concerns for secondary education pupils were concentration, motivation and work pace (Smeets et al., 2019). These results have been confirmed by de Boer and Kuijper (2021). Pupils with special needs within regular education, despite only having a specific learning disorder, tend to have problems with concentration and learning strategies as well (de Boer & Kuijper, 2021).

Preconditions for learning also differ for primary and secondary education. The decrease in school motivation of pupils in secondary education has been well documented. There have been concerns about the decrease in pupils' school motivation following school transitions such as primary to secondary education (van der Veen & Peetsma, 2020). Research from four countries showed that pupils' motivation also decreases during adolescence (Peetsma et al., 2005). On top of this, there is a steady decrease in pupils' intrinsic motivation through third to eighth grade (ages 8-14) (Corpus et al., 2009). Whereas for the primary school years dysfunctional learning behaviour decreases each year, it increases from the age of 11 (Schaefer, 2004). The increasing dysfunctional learning behaviour includes a lack of concentration and perseverance. The decrease in school motivation during the beginning of secondary education coincides with a decrease in pupil performance (Wijsman et al., 2016).

Cluster analysis

In this study cluster analysis was applied, which is a statistical method used to discover profiles. Cluster analysis has been extensively used for discovering interesting patterns in seemingly random data (Serban & Jiang, 2012). Clusters of participants can be characterized by mean scores on the input variables: these line plots of mean scores are usually referred to as profiles. Cluster analysis is a valuable tool set for uncovering underlying mechanisms in heterogeneous data (Vervoort et al., 2022). When using cluster analysis with preconditions for learning as input variables, different profiles could emerge. An example of a profile of the learning preconditions is pupils having high motivation and concentration, but low work pace. Another example is having low motivation, high concentration and high work pace. Studying profiles provides us insight into what profiles typically occur among pupils.

Cluster analysis using the learning preconditions of secondary special needs pupils could help identify patterns within the learning preconditions of pupils. Insight into profiles of learning preconditions may provide leads for personalized help (Radema & van Kessel, 2016). Preconditions for learning are proven to be relevant in both regular secondary education as well as special needs education. As mentioned above, learning preconditions like concentration and motivation affect learning in a number of different ways. Profiles of these learning preconditions may help connect the individual learning preconditions and give an overview of pupils' learning.

Profiles of motivation dimensions have been studied in literature. These profiles are different combinations of mastery, performance, social and extrinsic motivation. Research either found four or six different profiles in motivation (Blom et al., 2021; Korpershoek et al., 2015). Profiles that have been found in these studies are typically one profile with high mean scores on all types of motivation and one profile with low mean scores on all types of motivation. In addition, multiple other profiles were discovered. The relationship between the profiles of motivation dimensions and pupils' educational outcomes has also been explored (Korpershoek et al., 2015). Findings show a positive connection between the different types of motivation with school commitment and academic self-efficacy. These outcomes show how profiles can correlate to school performance.

Current study

Profiles of preconditions for learning have not been comprehensively studied. Profiles of school motivation have been investigated for regular secondary education pupils only (Blom et al., 2021; Chittum & Jones, 2017; Korpershoek et al., 2015). Furthermore, profiles of motivation dimensions or other learning preconditions have also not been comprehensively researched for pupils with special educational needs. In this study, cluster analysis will be employed to explore profiles of cognitive learning preconditions in a sample of secondary special needs education pupils.

The research question is: which profiles of cognitive preconditions for learning can be identified for pupils of secondary special needs education?

Based on the literature overview presented above, we have the following hypotheses. First of all, in correspondence with other research, we expect one profile of pupils with high mean scores on all preconditions for learning and one profile of pupils with low mean scores on all learning preconditions (Blom et al., 2021; Korpershoek et al., 2015). We also expect various profiles with low levels of motivation, regardless of the mean score on the other preconditions for learning, since motivation tends to be generally low in secondary education (Corpus et al., 2009; Peetsma et al., 2005; van der Veen & Peetsma, 2020). A substantial correlation between the mean scores of task orientation and planning is also expected, because the definitions of these learning preconditions are very similar.

Method

Research design

The design was descriptive research, non-experimental. Pupils weren't assigned to any conditions. The data has been collected on seven special needs education schools over a period of five years, resulting in one group with multiple cohorts. Research was cross-sectional, changes over time have not been investigated. The data used in this study were part of a larger research project of the University of Groningen in cooperation with an educational institute. Funding originated from NRO Programmaraad Praktijkgericht Onderzoek (PPO). Permission for the data collection and research was acquired from the Ethics Committee of the Faculty of Behavioural and Social Sciences on November 2, 2021 (PED-2021-S-0094).

Sample

The total sample consisted of 1580 pupils of seven cluster 4 schools. Each participating school was located in the northern provinces of the Netherlands (Groningen, Friesland and Drenthe). There were no missing data for the questions about the preconditions for learning. However, of the pupils, one registered as four years of age and four pupils were 116 years or older. The reason for the outliers was quite likely administrative errors: typos, the pupils have been removed from the sample. The final sample was N = 1575 pupils with a range of age between 11.51 and 21.11 (M = 15.18). 77% of the pupils were male and two pupils had missing gender. The pupils were following education on seven special needs schools in the school years 2016-2017, 2017-2018, 2018-2019, 2019-2020 and 2020-2021.

The education offered at the seven schools differed per school. Two schools specified their goal as preparing pupils for regular education, vocational education or (protected) labour. Three schools offered vocational education and labour after their school. Two schools also offered havo and VWO together with vocational education. One of the two could even prepare pupils for labour. Internships for pupils were also offered at most schools. Some schools were located together or working together with a regular education secondary school and a school for vocational education, resulting in easier transitions offered between the three types of education. In the school year 2021-2022 between 58 and 201 pupils (M = 126) were enrolled in each individual school.

Population

The sample from this research could be representative of all secondary cluster 4 schools in the northern three provinces of the Netherlands. The participating schools were located in different cities of the three northernmost provinces of the Netherlands (i.e., Groningen, Friesland and Drenthe). The researchers had no influence on which pupils and which schools were assessed. There were other secondary special needs schools in these provinces as well, also cluster 4 schools.

Procedure

The data have been collected using the questionnaire ‘Leervoorwaardentest’ (Preconditions for learning test). Pupils were assessed during the school years 2016-2017, 2017-2018, 2018-2019, 2019-2020 and 2020-2021. Assessment took place at school by a teacher or an internal support coordinator and was done to monitor pupil’s development. Pupils enrolled for multiple years might have taken the questionnaire multiple times. If a pupil had taken the questionnaire during multiple school years, a random entry was chosen. The other assessments of that particular pupil have not been included in the sample.

Variables

The full questionnaire contained 70 questions distributed over ten subscales. These subscales were motivation (Mo), task orientation (TO), concentration (Co), planning (Pl), work pace (WP), perseverance (Pe), social position, social orientation, relationship with the teacher and relationship with classmates. For this research, only the first six, known as the cognitive preconditions for learning (CL), have been used. The reliability and validity for the questionnaire have previously been examined for Dutch primary and secondary education (Scholte & Van der Ploeg, 2011). Parents and teachers participated in this study. Here, only the findings for teachers as the person assessing the pupils' behaviour from Scholte and Van der Ploeg (2011) are reported. Reliability was estimated using Cronbach's alpha.

Some reliability and validity results found by Scholte and Van der Ploeg (2011) are shown in Table 1. The construct validity was assessed using the correlation between the subscales and the overall scale cognitive preconditions for learning. The correlations between the subscales and the disorder are separately shown for various disorders (ADHD, ODD/CD and autism). The inter-rater reliability for the overall scale was measured for special needs education. All reliability statistics are considered high (Henson, 2001).

Each of the six subscales consists of seven items with five answer options each. The answer options range from 1 '(almost) never' to 5 '(almost) always'. Most items are phrased positively, meaning answer options 1 meant a low amount of cognitive learning precondition and answer option 5 meant a high amount of cognitive learning precondition. The subscales with negatively phrased items were concentration, work pace and perseverance. In the end the answer options of the positively phrased items were inverted, resulting in a low score for a cognitive precondition reflecting a more favourable image of learning. For each subscale, the scores for all seven items were added, resulting in the six subscales. The same was done for the subscales, resulting in the overall scale.

Table 1

Reliability, validity and correlations for cognitive learning preconditions

	Estimated reliability	Item rest correlations	Inter-rater reliability	Test-retest reliability	Construct validity	ADHD	ODD/CD	Autism
CL	0.98	0.47-0.83	0.88	0.84				
Mo	0.94	0.76-0.86	0.80	0.84	0.85	0.52	0.46	0.40
TO	0.94	0.75-0.85	0.83	0.88	0.94	0.62	0.44	0.38
Co	0.91	0.64-0.83	0.84	0.83	0.92	0.74	0.48	0.37
Pl	0.93	0.75-0.84	0.89	0.82	0.94	0.63	0.36	0.41
WP	0.90	0.63-0.84	0.81	0.83	0.83	0.44	0.15	0.34
Pe	0.91	0.62-0.84	0.80	0.87	0.91	0.71	0.46	0.41

Each subscale has items either phrased positively or negatively. Motivation was the first subscale. Example items for this scale were: ‘werkt met veel plezier’ (works with great pleasure) and ‘is gemotiveerd voor school’ (is motivated for school). Task orientation was the second subscale. An example of an item in this subscale was: ‘werkt grondig en nauwgezet’ (works thoroughly and meticulously). For the third subscale, concentration, two items were phrased negatively. An example being: ‘wordt door het minste of geringste afgeleid’ (is distracted by the slightest thing). A positively phrased item was: ‘kan aandacht langdurig op werk richten’ (can focus attention on work for a long time). Planning was the fourth subscale. Example item was: ‘neemt initiatieven bij het werken’ (takes initiative when working). For the fifth subscale, work pace, two items were phrased negatively. Example being: ‘werkt langzaam' (works slowly). The other five items were phrased positively. Example being: 'heeft een hoog werktempo' (has a high work pace). The sixth and last subscale was perseverance. Four items were phrased negatively. An example was: 'heeft aansporing nodig om aan iets te beginnen of iets af te maken' (needs incentive to start or finish something). The other three items were phrased positively. Example being: 'werkt lang achter elkaar door' (works for a long time).

Analysis plan

The analyses were done in two parts. The first part consisted of analyses done in SPSS Statistics 26. The second part was cluster analysis done in LatentGOLD version 5.0. The analyses done in SPSS included descriptive statistics, Cronbach's alpha, correlations between the items within the subscales and correlations between the subscales. The descriptive statistics included mean, minimum, maximum and standard deviation for each subscale and for cognitive preconditions for learning in general, as well as for age. These statistics were examined to obtain a better understanding of the data. The reliability was estimated using Cronbach's alpha where $\alpha < .70$ was interpreted as low, $.70 < \alpha < .80$ as acceptable and $\alpha >.80$ as high (Henson, 2001). The reliability of the subscales was also examined if certain items were deleted. If the reliability increased when deleting an item, it was reason for concern. The next analyses were the correlations between the items within a subscale, between the subscales and between a subscale and the overall scale, cognitive preconditions for learning. For correlations Pearson's r was used. The criteria for correlations were: $r < 0.3$ indicated low linear association, $0.3 > r > 0.6$ is moderate and $r > 0.6$ is high linear association (Odom & Morrow, 2006).

The second part contained the main analysis. Different clustering models were run. The input variables were motivation, task orientation, concentration, planning, work pace and perseverance. Each variable level was set to 'continuous'. The value of 'random sets' was set to 200. Models with one to 17 different clusters were explored. To determine the optimal number of clusters, the fit of these 17 models was compared using the BIC and CAIC. These two indices have been widely researched as indices for statistical model selection (cf. Burnham & Anderson, 2004). By running simulations the BIC was found to be the best index across different models and sample sizes (Nylund et al., 2007). The lowest number for both measures indicated the optimal model, i.e., optimal number of clusters. The optimal model was also run using gender as a covariate. This analysis provided the percentage boys in each cluster.

Interpretation of the clusters was done using the average scores for the different learning preconditions for each cluster. These scores were compared to the scores of the norm table found in the instruction manual for the preconditions for learning test (Scholte & Van der Ploeg, 2011). For this research the norm table using teachers as assessors was used. Also, only male pupils ages 12-18 have been incorporated. Since the sample mostly consisted of male pupils, the decision to only use the norm table for male pupils was made.

Results

Descriptive statistics

Table 2 presents descriptive statistics for the overall scale cognitive learning preconditions, the subscales motivation, task orientation, concentration, planning, work pace, perseverance and age. The average score of the overall scale cognitive preconditions for learning is $M = 133.97$ ($SD = 36.99$). The average score of the overall scale and the six subscales all have the classification normal according to the norm table.

Table 3 presents, for the overall scale and the subscales, the reliability if an item was deleted. For the overall scale these items are the six subscales. For the subscales these items are the individual questions. Cronbach's alpha for the overall scale cognitive preconditions for learning is high ($\alpha = .964$). For none of the subscales the estimated reliability increased if one of the items was deleted. The lowest Cronbach's alpha is for work pace ($\alpha = .890$) and the highest is for motivation ($\alpha = .954$). The estimated reliability for each subscale is considered high (Henson, 2001).

Table 4 presents the correlations between the overall scale and the subscales. All correlations shown are significant at the 0.01 level. Between the different subscales and overall scale cognitive learning preconditions, the correlations are considered high ($r > .889$). The lowest correlation between the subscales is between concentration and motivation ($r = .728$) and the highest correlation is planning and motivation with task orientation ($r = .886$). All correlations are considered high, meaning a high score on one subscale would most likely suggest a high score on another subscale.

Table 2

Descriptive statistics of age, overall scale and subscales and reliability (N = 1575)

	Minimum	Maximum	M	SD	Alpha
Age	11.51	21.11	15.18	1.60	
CL	42	209	133.97	36.99	.964
Mo	7	35	23.14	7.00	.954
TO	7	35	21.99	7.07	.949
Co	7	35	21.62	6.32	.896
Pl	7	35	24.11	6.42	.925
WP	7	35	21.59	6.28	.890
Pe	7	35	21.52	7.02	.924

Table 3

Cronbach's alpha if item deleted for overall scale and subscales

	CL		Mo	TO	Co	Pl	WP	Pe
Mo	.963	1	.947	.941	.871	.908	.879	.917
TO	.952	2	.946	.943	.888	.917	.862	.912
Co	.958	3	.945	.941	.875	.914	.867	.908
Pl	.954	4	.948	.938	.871	.913	.861	.914
WP	.959	5	.948	.937	.882	.909	.880	.913
Pe	.958	6	.944	.944	.891	.916	.881	.914
		7	.948	.941	.890	.919	.883	.912

Table 4

Correlations between overall scale and subscales (N = 1575)

	CL	Mo	TO	Co	Pl	WP	Pe
CL	-						
Mo	.889	-					
TO	.955	.886	-				
Co	.914	.728	.847	-			
Pl	.941	.798	.886	.844	-		
WP	.911	.731	.820	.808	.861	-	
Pe	.922	.755	.835	.845	.823	.837	-

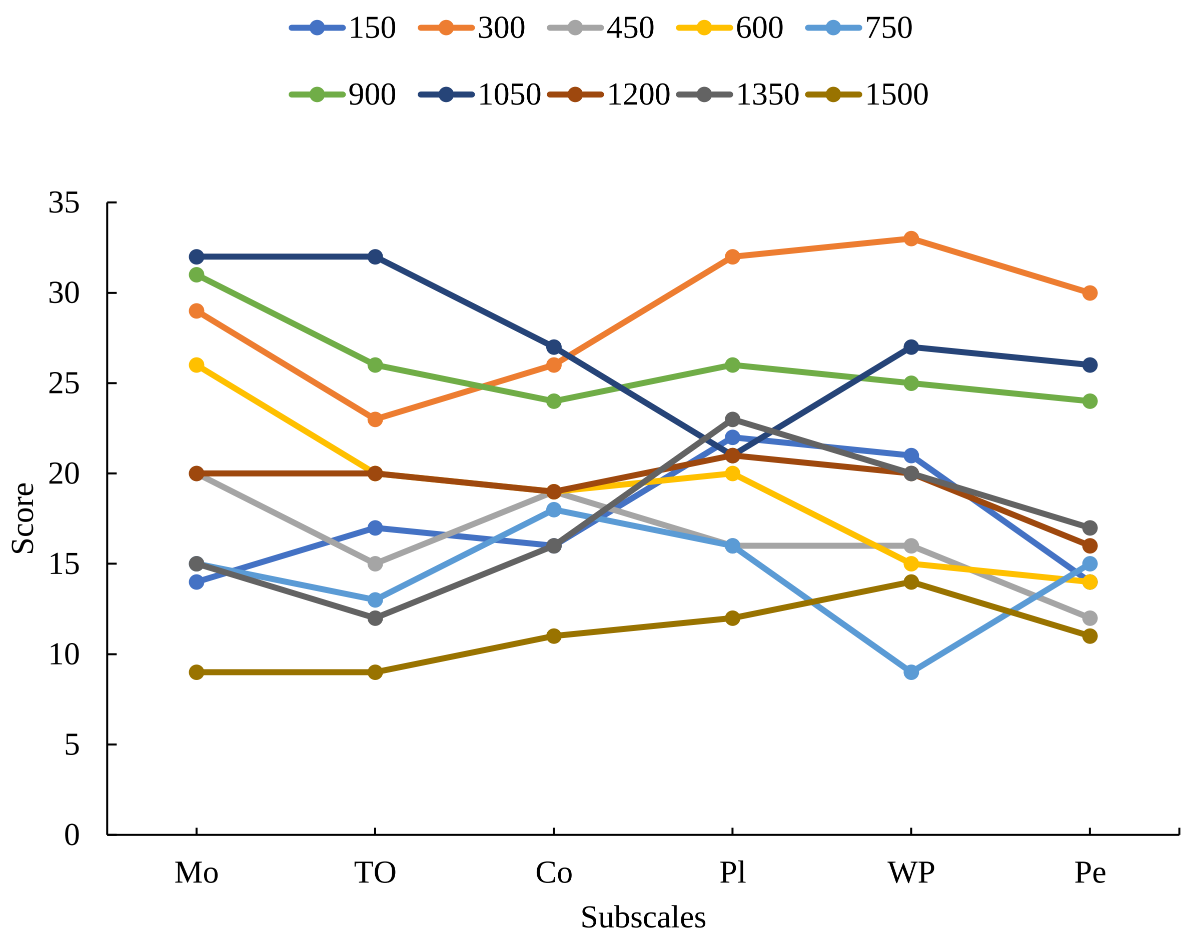

Figure 1. Mean scores on subscales for 10 random pupils

Means for 10 random pupils

To take a look at the data before arranging the pupils in clusters, 10 pupils have been randomly chosen. Figure 1 presents, for the individual pupils, the scores for the six subscales. It can be seen that pupils score very differently from each other. Some pupils portray a varied image on the cognitive preconditions for learning with, for example, high mean scores on motivation and task orientation, but a lower mean score on planning. Other pupils show a more consistent image. These pupils score roughly the same on all six subscales, for example pupil 1200.

Cluster analysis

Table 5 presents various indices for model fit evaluation associated with the 17 models. For the CAIC the lowest value was found for the model with 13 clusters. For the BIC, however, the lowest value could be found for the model with 14 clusters. So, at first, on the basis of the indices, no clear best model could be identified. Therefore, both the 13-cluster model and the 14-cluster model are examined to determine similarities and possible differences.

Table 5

Various indices for model fit evaluation

K	Log-likelihood	BIC	CAIC	Classification errors	Entropy R-squared	Standard R-squared
1	-31347.7	62783.66	62795.66	0	1	1
2	-28112.6	56409.15	56434.15	0.024	0.920	0.932
3	-26872.6	54025.02	54063.02	0.039	0.914	0.913
4	-26196.2	52767.87	52818.87	0.056	0.903	0.891
5	-25779	52029.26	52093.26	0.054	0.911	0.895
6	-25548.6	51664.01	51741.01	0.076	0.892	0.862
7	-25405.8	51474.09	51564.09	0.099	0.872	0.829
8	-25313.7	51385.77	51488.77	0.113	0.863	0.809
9	-25227.0	51307.96	51423.96	0.121	0.855	0.799
10	-25148.9	51247.55	51376.55	0.131	0.849	0.785
11	-25073.8	51193.05	51335.05	0.139	0.846	0.774
12	-25006.6	51154.37	51309.37	0.145	0.845	0.767
13	-24939.5	51115.82	**51283.82**	0.147	0.845	0.765
14	-24887.4	**51107.29**	51288.29	0.149	0.847	0.764
15	-24841.4	51110.99	51304.99	0.151	0.848	0.762
16	-24810.9	51145.81	51352.81	0.168	0.835	0.739
17	-24782.2	51183.98	51403.98	0.157	0.846	0.755

Note. K = the number of clusters. Bold indicated best fit according to BIC or CAIC.

Comparing 13-cluster and 14-cluster model

Table 6 presents various statistics of the 13-cluster model and the 14-cluster model. First there is the range of mean subscale scores. This statistic shows the difference between the highest and lowest means of the subscales. If a cluster has a pattern of means around the same score for each subscale, the range will be small. However, if a cluster has a high mean on, for example, planning and a low mean for work pace, the range will be large. After comparing the two models on range, some clusters seem to be the same for both models. Cluster 12 of the 13-cluster model and Cluster 14 of the 14-cluster model form an example. These two clusters both have a range of around 8, which is the largest range among the clusters. The smallest range of both models can also be matched. This corresponds to Cluster 13 of the 13-cluster model and Cluster 12 for the 14-cluster model. These clusters have a range of 1.81 and 1.70 respectively.

Table 7 and 8 present the mean score for each subscale and cluster sizes for both the 13-cluster model and the 14-cluster model. The same mean scores are also shown in Figure 2 and 3. Each cluster has a line connecting the mean scores for each subscale. Table 6 shows the largest cluster of the 13-cluster model is 0.1441 and the smallest is 0.0317. For the 14-cluster model, the largest cluster is 0.1328 and the smallest cluster is 0.0271. Both the smallest and the largest cluster for the 14-cluster model are smaller than the 13-cluster model. However, as the same sample has to be distributed over one extra cluster, this is not surprising. The 13-cluster model is not more desirable on the basis of cluster size.

No clear model is superior to the other on numerous measurements. As mentioned before, the BIC is usually considered superior to the CAIC (Nylund et al., 2007). Therefore, the 14-cluster model, the optimal model according to the BIC, will be considered in more detail.

Table 6

Comparison of 13-cluster and 14-cluster model on different statistics

	13-cluster model			14-cluster model		
	Min. - Max.	Mean	Range	Min. - Max.	Mean	Range
1	17.38 –20.32	18.65	2.94	20.99 – 25.00	22.83	4.01
2	20.53 – 24.39	22.22	3.86	27.70 – 29.69	28.20	2.74
3	23.05 – 27.64	25.23	4.60	23.00 – 27.78	25.35	4.78
4	27.25 – 30.19	28.80	2.94	18.92 – 22.22	20.53	3.30
5	25.28 – 29.11	26.82	3.83	16.30 – 19.86	17.67	3.56
6	20.16 – 23.95	21.83	3.79	24.04 – 28.32	25.86	4.28
7	10.07 – 14.47	12.37	4.41	29.66 – 32.21	30.92	2.55
8	13.97 – 17.22	15.17	3.25	9.952 – 14.43	12.31	4.47
9	13.95 – 19.75	16.47	5.79	17.39 – 21.85	19.94	4.46
10	30.47 – 32.78	31.61	2.31	13.41 – 19.63	16.04	6.23
11	7.61 – 9.95	8.94	2.34	13.61 – 16.52	14.75	2.91
12	25.07 – 33.07	28.44	8.00	32.80 – 34.50	33.66	1.70
13	32.70 – 34.51	33.84	1.81	7.59 – 9.91	8.92	2.32
14	-	-	-	25.04 – 33.21	28.45	8.16

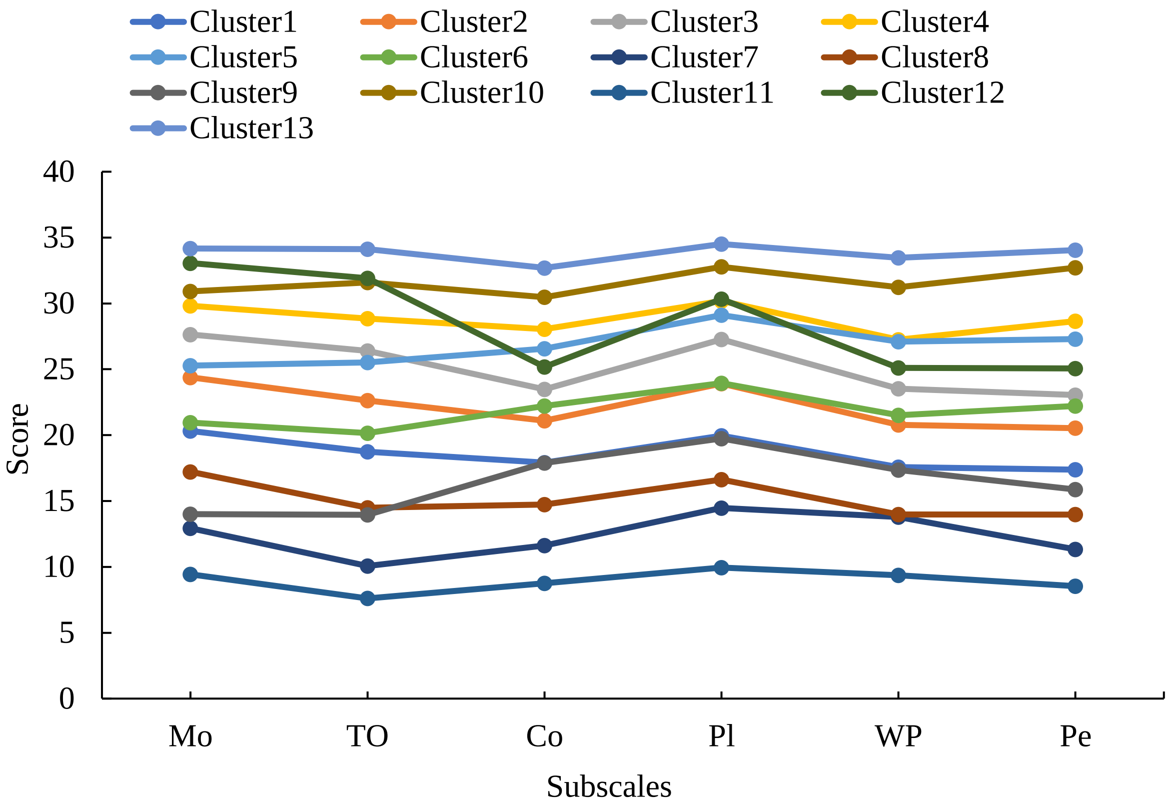

Figure 2. Profile plot (means) of 13-cluster model

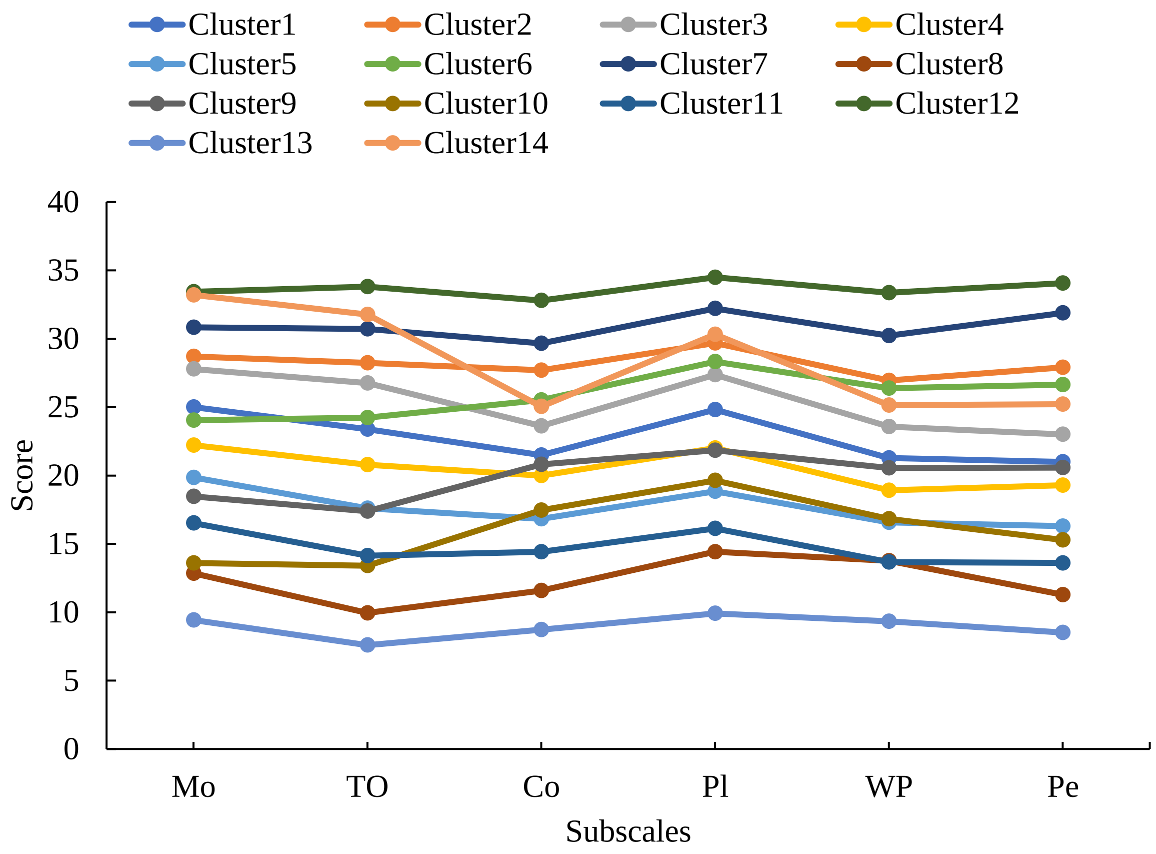

Figure 3. Profile plot (means) of 14-cluster model

Table 7

13-cluster model mean score for each subscale and cluster sizes

	Cluster size	Mean score						
		CL	Mo	TO	Co	Pl	WP	Pe
1	0.144	111.90	20.32	18.75	17.92	19.96	17.57	17.38
2	0.130	133.35	24.39	22.64	21.10	23.92	20.77	20.53
3	0.101	151.37	27.64	26.39	23.48	27.27	23.53	23.05
4	0.099	172.81	29.83	28.84	28.05	30.19	27.25	28.65
5	0.099	160.90	25.28	25.53	26.57	29.11	27.10	27.30
6	0.098	130.99	20.95	20.16	22.22	23.95	21.50	22.21
7	0.067	74.23	12.92	10.07	11.64	14.47	13.79	11.34
8	0.064	91.03	17.22	14.48	14.74	16.63	13.98	13.97
9	0.048	98.84	14.02	13.95	17.90	19.75	17.35	15.87
10	0.046	189.67	30.91	31.59	30.47	32.78	31.22	32.70
11	0.041	53.65	9.45	7.61	8.75	9.95	9.36	8.55
12	0.032	170.66	33.07	31.91	25.18	30.32	25.11	25.07
13	0.032	203.02	34.18	34.13	32.70	34.51	33.45	34.05

Table 8

14-cluster model mean score for each subscale and cluster size

	Cluster size	Mean score						
		CL	Mo	TO	Co	Pl	WP	Pe
1	0.133	136.97	25.00	23.39	21.50	24.81	21.28	20.99
2	0.128	169.19	28.71	28.23	27.70	29.69	26.95	27.92
3	0.112	152.10	27.78	26.77	23.62	27.36	23.57	23.00
4	0.086	123.20	22.22	20.78	19.99	22.01	18.92	19.28
5	0.084	106.02	19.86	17.61	16.84	18.85	16.56	16.30
6	0.082	155.17	24.04	24.24	25.52	28.32	26.39	26.65
7	0.066	185.53	30.82	30.73	29.66	32.21	30.23	31.88
8	0.064	73.88	12.86	9.95	11.58	14.42	13.77	11.29
9	0.057	119.64	18.46	17.39	20.80	21.84	20.56	20.58
10	0.053	96.21	13.59	13.41	17.46	19.63	16.84	15.27
11	0.048	88.48	16.52	14.14	14.42	16.12	13.67	13.61
12	0.031	201.97	33.44	33.80	32.80	34.50	33.37	34.07
13	0.029	53.52	9.427	7.59	8.73	9.91	9.33	8.52
14	0.027	170.70	33.21	31.76	25.04	30.33	25.14	25.23

Note. = favourable = normal = unfavourable

14-cluster model

Figure 3 presents the profile plot for the 14-cluster model. It can be seen that most clusters show the same pattern, with an almost straight horizontal line across all cognitive preconditions for learning, indicating that the mean scores of the subscales are roughly the same. This pattern can also be seen in Table 6. Table 6 presents the ranges for the 14-cluster model. Five of the 14 cluster have a range below 3 score points. Twelve have a range below 5 score points.

The average scores also differ greatly between the clusters and subscales. The scores for each subscale range from 7 to 35. Table 8 presents the mean scores for the subscales for each cluster. When using the norm table, scores can be divided into three big groups: favourable, normal and unfavourable. For motivation scores 18 or lower means favourable (#K = 5), the group normal is between mean scores 19-26 (#K = 4) and scores 27 or higher means unfavourable (#K = 5). For task orientation scores 19 or lower suggests favourable (#K = 6), normal is between 20-27 (#K = 4) and scores 28 or higher suggests unfavourable (#K = 4). For concentration scores 18 or lower means favourable (#K = 5), normal is between 19-26 (#K = 6) and scores 27 and higher means unfavourable (#K = 3). For planning scores 21 or lower suggests favourable (#K = 6), normal is between 22-28 (#K = 4) and 29 or higher suggests unfavourable (#K = 4). For work pace scores 18 or lower means favourable (#K = 6), normal is between 19-25 (#K = 4) and scores 26 or higher means unfavourable (#K = 4). For perseverance scores 17 or lower suggest favourable (#K = 5), normal is between 18-25 (#K = 5) and scores 26 or higher suggests unfavourable (#K = 4). The same can be done using the accumulative score of the overall scale. Scores 116 or lower means favourable (#K = 5), scores between 117 and 157 are considered normal (#K = 5) and scores 158 or higher means unfavourable (#K = 4). As can be seen by the number of clusters per group, the clusters are dispersed very evenly for each subscale separately with a minimum of three clusters in one group and a maximum of six clusters. When investigating all six subscales together, eight clusters score the same on all six subscales. With four clusters all scoring favourable (K = 8, 10, 11 and 13), one clusters all scoring normal (K = 1) and three clusters all scoring unfavourable (K = 2, 7 and 12).

The 14-cluster model was also run using gender as covariate. For the full sample 77% is male. Table 9 shows the distribution of male and female for each cluster. The most remarkable difference exists for cluster 9. For this cluster, the percentage male is as low as 57%, which is the lowest percentage of males across the clusters. However, for no cluster the percentage of females is higher than the percentage of males.

Table 9

Distribution of male and female for each cluster within the 14-cluster model

	1	2	3	4	5	6	7
Female	0.1912	0.2311	0.1788	0.1293	0.3055	0.1659	0.3005
Male	0.8088	0.7689	0.8212	0.8707	0.6945	0.8341	0.6995
	8	9	10	11	12	13	14
Female	0.2257	0.4304	0.1745	0.2607	0.3375	0.2988	0.1386
Male	0.7743	0.5696	0.8255	0.7393	0.6625	0.7012	0.8614

Discussion

Conclusion

The current research investigated the notion of profiles within the cognitive preconditions for learning. The following research question was explored: which profiles of cognitive preconditions for learning can be identified for pupils of secondary special needs education? A 14-cluster model was found to be the optimal model for the data. Most of the 14 clusters showed the same pattern of roughly similar mean scores on all six cognitive preconditions for learning. This suggests that many pupils with a high mean score on one learning precondition, also have high mean scores on the other learning preconditions. The clusters were dispersed evenly among the possible range of score on cognitive learning preconditions. When comparing the mean scores for each cluster with the norm table, it was found that the clusters are dispersed among the groups favourable, normal and unfavourable evenly. The groups are approximately equally represented. This suggests all types of pupils, in regards to the learning preconditions, can be found in special needs education.

Previous research suggested problems with cognitive preconditions for learning for secondary education and special needs education (Corpus et al., 2009; de Boer & Kuijper, 2021; Peetsma et al., 2005; Schaefer, 2004; Smeets et al., 2019; van der Veen & Peetsma, 2020). Given the norm table, the clusters are dispersed evenly among the groups favourable, normal and unfavourable. This seems contrary to previous research which suggested secondary special needs pupils have more problems with cognitive preconditions for learning than their regular education peers. Since the norm table was based on regular education and not special needs education, more clusters showing unfavourable learning preconditions were expected. This research gives new perspective on the level of cognitive preconditions for learning of secondary special needs education pupils.

Only two clusters deviated from the common pattern of roughly similar mean scores across the subscales. The first cluster has the highest score on planning and lowest score on motivation, however, all mean scores of this particular cluster are considered favourable according to the norm table. For the other cluster, three subscales have normal mean scores and three subscales have unfavourable mean scores. The unfavourable mean scores are for motivation, task orientation and planning.

Hypotheses made were, first of all, one cluster with general high mean scores and one cluster with general low mean scores. This turned out to be in line with the results. The highest mean scores can be seen in one cluster and the lowest mean scores can be seen in another. Both clusters also have a low range, meaning all mean scores are close together. Another hypothesis made was: various clusters have low levels of motivation, regardless of other mean scores. For motivation there are five clusters classified as unfavourable according to the norm table. Thus, evidence for this hypothesis was also provided. The last hypothesis made was: correlation between task orientation and planning is high. The correlation between the two subscales is .886. This is the highest correlation between any two subscales.

Contributions

The current study had several strong features. First the sample originated from various schools, spread evenly throughout the north of the Netherlands. This makes the sample's representativeness for the north of the Netherlands reasonable. Collecting the data over a period of five years ensures that no occurrence during a specific year skewed the data terribly. Also, there was no missing data, every questionnaire was completely answered. Therefore, no analysis of missing data was necessary.

The correlations of the scales used in this study was very high. This supports the existence of the overall scale. The reliability of the scales is also very high. The same results have been found in the manual of the questionnaire (Scholte & Van der Ploeg, 2011). This research also discussed secondary special needs education, but not in great detail. The current research provided evidence supporting the current use of the cognitive preconditions for learning of the questionnaire ‘Leervoorwaardentest’ on secondary cluster 4 schools.

Limitations

The collection of data had some limitations. First the school year 2020-2021 was a year in which the schools were closed for multiple weeks due to the COVID-19 pandemic. This may have influenced the assessment of pupils. Not only would the timing have been different, some pupils might not even have been tested during that year. This could have resulted in a smaller and less representative sample. The pupil’s cognitive preconditions for learning might also have decreased due to home-schooling. Children with developmental disorders experienced the period of learning from home more negatively than children without a developmental disorder (Baten et al., 2022). If only pupils assessed during 2020-2021 were considered, more clusters might have been unfavourable. However, the data has been collected during five years, which resulted in the majority of pupils not being assessed during the school year 2020-2021. So, presumably the impact of COVID-19 was small.

Another limitation of the current study is the sample. The schools are all part of the north of the Netherlands. If the north of the Netherlands should only be represented, the sample was likely sufficient. However, nothing could be said on the basis of the sample about the Netherlands as a whole. The data was also not randomly obtained. Data was not collected for the purpose of research, but for personal use on school. Therefore, the schools and especially the pupils have not been specifically chosen for the study. This may have influenced the representativeness of the sample to some extent.

The use of cluster analysis also comes with limitations. Only one cluster analysis method was used, even though there are many clustering methods, based on various different approaches (Jain, 2010). Using other clustering methods for the same data usually leads to other clusters (Hennig, 2016). This research only considered two possible cluster solutions obtained with the same clustering method. No comparison was made between different methods, which could have led to a better understanding of the data.

Recommendations

Some recommendations for future research can be made. Future research should use a sample collected randomly from the whole of the Netherlands. This may ensure that the sample represents the whole of the Netherlands properly, not only the northern three provinces of the Netherlands. Future research should also use multiple methods of cluster analysis. This will ensure different cluster solutions are represented and researched. Implementing a cluster analysis means making numerous choices (Jain, 2010). Some of these choices have not been explored comprehensively in this research. Examples of choices are, which indices to use to select the number of clusters, which software to use and which clustering method. Future research should study these choices and could even compare different methods, not only apply them. This will probably provide a better understanding of the data at hand, as well as of the clustering methods used.

The results of this research can also give information for secondary special needs education. In recent years, the questionnaire ‘Leervoorwaardentest’ has been commonly used on secondary special needs education. The results from this research support the current use of the questionnaire on these schools. No evidence was found to the contrary. This research also shows the normal pattern of mean scores of the clusters to be roughly the same score on all cognitive preconditions for learning. It can be thought that, in practice, it might not be useful to measure each cognitive learning precondition to know how a pupil is performing on the cognitive learning preconditions. The level of concentration of a pupil can perhaps be derived from the level of work pace of the pupil. However, all the cognitive learning preconditions are still useful. The ten individual pupils show a more varied image of the cognitive preconditions for learning. So, measuring all cognitive learning preconditions give a more varied image than only measuring one.

Bibliography

Akos, P., & Kretchmar, J. (2017). Investigating Grit at a Non-Cognitive Predictor of College Success. *Review of Higher Education*, *40*(2), 163-186. https://doi.org/http://dx.doi.org/10.1353/rhe.2017.0000

Baten, E., Vlaeminck, F., Mués, M., Valcke, M., Desoete, A., & Warreyn, P. (2022). The Impact of School Strategies and the Home Environment on Home Learning Experiences During the COVID-19 Pandemic in Children With and Without Developmental Disorders. *Journal of Autism and Developmental Disorders*. https://doi.org/10.1007/s10803-021-05383-0

Best, J. R., Miller, P. H., & Naglieri, J. A. (2011). Relations between executive function and academic achievement from ages 5 to 17 in a large, representative national sample. *Learning and Individual Differences*, *21*(4), 327-336. https://doi.org/10.1016/j.lindif.2011.01.007

Blom, D. M., Warrens, M. J., & Faber, M. (2021). School motivation profiles of Dutch 9th graders. *Communications in Statistics: Case Studies, Data Analysis and Applications*, *7*(3), 359-381. https://doi.org/10.1080/23737484.2021.1911719

Burnham, K. P., & Anderson, D. R. (2004). Multimodel Inference. *Sociological Methods & Research*, *33*(2), 261-304. https://doi.org/10.1177/0049124104268644

Chittum, J. R., & Jones, B. D. (2017). Identifying Pre-High School Students' Science Class Motivation Profiles to Increase Their Science Identification and Persistence. *Journal of Educational Psychology*, *109*(8), 1163-1187. http://dx.doi.org/10.1037/edu0000176

Clark, K. N., Dorio, N. B., Eldridge, M. A., Malecki, C. K., & Demaray, M. K. (2020). Adolescent Academic Achievement: A Model of Social Support and Grit. *Psychology in the Schools*, *57*(2), 204-221. http://dx.doi.org/10.1002/pits.22318

Corpus, J. H., McClintic-Gilbert, M. S., & Hayenga, A. O. (2009). Within-year changes in children's intrinsic and extrinsic motivational orientations: Contextual predictors and academic outcomes. *Contemporary Educational Psychology*, *34*(2), 154-166. https://doi.org/10.1016/j.cedpsych.2009.01.001

Datu, J. A. D., Valdez, J. P. M., & King, R. B. (2016). Perseverance Counts but Consistency Does Not! Validating the Short Grit Scale in a Collectivist Setting. *Current Psychology*, *35*(1), 121-130. https://doi.org/10.1007/s12144-015-9374-2

de Boer, A., & Kuijper, S. (2021). Students' Voices about the Extra Educational Support They Receive in Regular Education. *European Journal of Special Needs Education*, *36*(4), 625-641. http://dx.doi.org/10.1080/08856257.2020.1790884

Duckworth, A. L., Peterson, C., Matthews, M. D., & Kelly, D. R. (2007). Grit: Perseverance and passion for long-term goals. *Journal of Personality and Social Psychology*, *92*(6), 1087-1101. https://doi.org/10.1037/0022-3514.92.6.1087

Friedman, N. P., Miyake, A., Young, S. E., Defries, J. C., Corley, R. P., & Hewitt, J. K. (2008). Individual differences in executive functions are almost entirely genetic in origin. *Journal of Experimental Psychology: General*, *137*(2), 201-225. https://doi.org/10.1037/0096-3445.137.2.201

Hennig, C., Meila, M., Murtagh, F., and Rocci, R. (2016). *Handbook of Cluster Analysis*. Chapman and Hall/CRC.

Henson, R. K. (2001). Understanding internal consistency reliability estimates: A conceptual primer on coefficient alpha. *Measurement and Evaluation in Counseling and Development*, *34*(3), 177-189. http://search.ebscohost.com.proxy-ub.rug.nl/login.aspx?direct=true&db=psyh&AN=2001-05693-005&site=ehost-live&scope=site

Jain, A. K. (2010). Data clustering: 50 years beyond K-means. *Pattern Recognition Letters*, *31*(8), 651-666.

Korpershoek, H., Kuyper, H., & Greetje. (2015). Differences in students' school motivation: A latent class modelling approach. *Social Psychology of Education*, *18*(1), 137-163. https://doi.org/10.1007/s11218-014-9274-6

Larson, C., Gangopadhyay, I., Prescott, K., Kaushanskaya, M., & Ellis Weismer, S. (2021). Planning in children with autism spectrum disorder: The role of verbal mediation. *Journal of Autism and Developmental Disorders*, *51*(7), 2200-2217. https://doi.org/10.1007/s10803-020-04639-5

Lockl, K., Attig, M., Nusser, L., & Wolter, I. (2021). Cognitive and Affective-Motivational Factors as Predictors of Students' Home Learning During the School Lockdown. *Frontiers in Psychology*, *12*, Article 751120. https://doi.org/10.3389/fpsyg.2021.751120

Manti, E., Scholte, E. M., & Van Berckelaer-Onnes, I. A. (2011). Development of children with autism spectrum disorders in special needs education schools in the Netherlands: a three-year follow-up study. *European Journal of Special Needs Education*, *26*(4), 411-427. https://doi.org/10.1080/08856257.2011.597172

Ministerie van Algemene Zaken. (2021). *Hoe lang mag mijn kind speciaal onderwijs volgen?* Retrieved February 22, 2022 from https://www.rijksoverheid.nl/onderwerpen/passend-onderwijs/vraag-en-antwoord/hoe-lang-mag-mijn-kind-speciaal-onderwijs-volgen

Ministerie van Onderwijs Cultuur en Wetenschap. (2021). *(Voortgezet) speciaal onderwijs*. Retrieved March 11, 2022 from https://www.rijksoverheid.nl/onderwerpen/passend-onderwijs/speciaal-onderwijs

Ministerie van Onderwijs Cultuur en Wetenschap. (2022). *Passend Onderwijs*. Retrieved March 25, 2022 from https://www.rijksoverheid.nl/onderwerpen/passend-onderwijs

Murayama, K., Pekrun, R., Lichtenfeld, S., & Vom Hofe, R. (2013). Predicting Long-Term Growth in Students' Mathematics Achievement: The Unique Contributions of Motivation and Cognitive Strategies. *Child Development*, *84*(4), 1475-1490. https://doi.org/10.1111/cdev.12036

Nylund, K. L., Asparouhov, T., & Muthén, B. O. (2007). Deciding on the Number of Classes in Latent Class Analysis and Growth Mixture Modeling: A Monte Carlo Simulation Study. *Structural Equation Modeling: A Multidisciplinary Journal*, *14*(4), 535-569. https://doi.org/10.1080/10705510701575396

Odom, L. R., & Morrow, J. J. R. (2006). What's this r? A Correlational Approach to Explaining Validity, Reliability and Objectivity Coefficients. *Measurement in Physical Education and Exercise Science*, *10*(2), 137-145. https://doi.org/10.1207/s15327841mpee1002_5

Peetsma, T., Hascher, T., van der Veen, I., & Roede, E. (2005). Relations between adolescents' self-evaluations, time perspectives, motivation for school and their achievement in different countries and at different ages. *European Journal of Psychology of Education*, *20*(3), 209-225. https://doi.org/10.1007/bf03173553

Pijl, S. J., Frostad, P., & Mjaavatn, P. E. (2014). Students with special educational needs in secondary education: are they intending to learn or to leave? *European Journal of Special Needs Education*, *29*(1), 16-28. https://doi.org/10.1080/08856257.2013.830442

Radema, D., & van Kessel, B. (2016). *In vijf stappen naar een onderwijszorgarrangement voor zmolk'ers [Brochure]*. https://www.nji.nl/system/files/2021-05/Brochure-in-vijf-stappen-naar-een-onderwijszorgarrangement-voor-zmolkers.pdf

Schaefer, B. A. (2004). A Demographic Survey of Learning Behaviors among American Students. *School Psychology Review, 33*(4), 481-497.

Scholte, E. M., & Van der Ploeg, J. D. (2011). *Leervoorwaardentest - Handleiding*. Springer. https://books.google.nl/books?id=D1CtzThJR7sC

Serban, N., & Jiang, H. (2012). Multilevel Functional Clustering Analysis. *Biometrics*, *68*(3), 805-814. https://doi.org/10.1111/j.1541-0420.2011.01714.x

Smeets, E., Ledoux, G., & van Loon-Dikkers, L. (2019). *Passend Onderwijs in De Klas: Tweede Meeting*. https://evaluatiepassendonderwijs.nl/wp-content/uploads/2019/06/56.-Passend-onderwijs-in-de-klas-2e-meting.pdf

Usán Supervía, P., & Salavera Bordás, C. (2020). Burnout, Goal Orientation and Academic Performance in Adolescent Students. *International Journal of Environmental Research and Public Health*, *17*(18), 6507. https://doi.org/10.3390/ijerph17186507

van der Veen, I., & Peetsma, T. (2020). Development of motivation in first-year students in Dutch senior secondary vocational education. *Educational Psychology*, *40*(8), 917-940. https://doi.org/10.1080/01443410.2019.1695748

van der Veen, I., Smeets, E., & Derriks, M. (2010). Children with special educational needs in the Netherlands: number, characteristics and school career. *Educational Research*, *52*(1), 15-43. https://doi.org/10.1080/00131881003588147

Vervoort, L., Naets, T., Goossens, L., Verbeken, S., Claes, L., Tanghe, A., & Braet, C. (2022). Subtyping youngsters with obesity: A theory-based cluster analysis. *Appetite*, *168*, Article 105723. https://doi.org/10.1016/j.appet.2021.105723

Wagner, M., & Davis, M. (2006). How Are We Preparing Students With Emotional Disturbances for the Transition to Young Adulthood? *Journal of Emotional and Behavioral Disorders*, *14*(2), 86-98. https://doi.org/10.1177/10634266060140020501

Wijsman, L. A., Warrens, M. J., Saab, N., Van Driel, J. H., & Westenberg, P. M. (2016). Declining trends in student performance in lower secondary education. *European*

Journal of Psychology of Education, *31*(4), 595-612. https://doi.org/10.1007/s10212-015-0277-2