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High-achieving students in mathematics: A heterogeneous group

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ABSTRACT

Although high-achieving students in mathematics are often regarded as a homogeneous group, there may be differences within this group. This study used a person-centred approach to investigate quantitative and qualitative differences between 625 high-achieving students (top 20 %) of Grades 3–6 in the Netherlands. Latent profile analyses were conducted based on a range of cognitive (nonverbal intelligence, verbal working memory and visual-spatial working memory), motivational (interest, perceived competence, and anxiety), and mathematics achievement (general mathematics achievement and arithmetic fluency) measures. Per grade, two to four latent profiles emerged (e.g., in Grade 3: 'relatively low on all variables', 'relatively uninterested very high achievers' and 'motivated'). While the variation on all variables was substantial, motivational variables contributed most to the distinction between the profiles. This heterogeneity among high-achievers implies that high-achieving students may have diverse educational needs to flourish and reach their full mathematical potential.

Educational relevance and implications statement

Primary school students who achieve highly in mathematics form a heterogeneous group, with varying strengths and weaknesses in cognitive, motivational, and mathematics achievement characteristics. Our findings show that not all high-achieving students have very high cognitive skills (although some do), feel very competent (although some do), or are very interested in mathematics (although some are). Moreover, the arithmetic fluency of some high-achieving students may be relatively underdeveloped. This also implies that different high-achieving students may have different educational needs. Textbook suggestions for differentiation for high achievers should not be implemented uncritically as a one-size-fits-all treatment. Instead, teachers should use their knowledge of their students and their professional competence to implement differentiation in a flexible way, attuned to the diverse needs of their high-achieving students.

1. Introduction

Research about high-achieving students in mathematics is relatively scarce (Myers et al., 2017). The available research often regards high-achieving students as a homogenous group, which is compared to average-achieving or low-achieving students (Bakker et al., 2022). However, there may be differences between high-achieving students, with consequences for their educational needs (Sjoers, 2018). Since the development of mathematical competencies involves a complex interplay between both general and specific cognitive abilities as well as motivational factors, a comprehensive approach is needed when examining differences between high-achieving students (Myers et al., 2017; Preckel et al., 2020). This study uses a person-centred approach to investigate whether latent profiles of high-achieving students can be distinguished based on a variety of cognitive, motivational and mathematics achievement characteristics. To this end, we re-analyse data from an existing dataset from which we selected high-achieving students of Grades 3 through 6 in Dutch primary schools.

1.1. Correlates of mathematics achievement

Previous research has identified a range of cognitive and motivational correlates and predictors of mathematics achievement (De Smedt, 2022; Gilmore, 2023; Myers et al., 2017; Preckel et al., 2020). Gilmore (2023) makes a distinction between general cognitive skills (e.g., working memory) and basic mathematical processes (e.g., non-symbolic number processing), which together contribute to students' proficiency with specific components of mathematics (e.g., arithmetic fluency). These specific components in turn make up students' general

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mathematics achievement. These cognitive and mathematical skills do not develop in a vacuum but interact with motivational factors such as perceived competence and with the learning environment, represented for example by parents and teachers (De Smedt, 2022; Gilmore, 2023; Myers et al., 2017; Preckel et al., 2020). While students' cognitive and motivational characteristics have traditionally been modelled as predictors of mathematics achievement, recent insights suggest that their relation with achievement is reciprocal; they are also predicted by previous achievement (De Smedt, 2022; Huang, 2011; Pekrun et al., 2017; Peng & Kievit, 2020). In the current study, we focus on a set of general cognitive factors (non-verbal intelligence, visual-spatial working memory and verbal working memory) and motivational factors (perceived competence, interest and anxiety) as relevant correlates of mathematics achievement (general mathematics achievement and arithmetic fluency as one of its component skills).

Regarding the general cognitive factors, intelligence and working memory are well-established positive correlates of mathematics achievement (De Smedt, 2022; Peng et al., 2016; Peng & Kievit, 2020). Fluid intelligence is considered an ability for abstract reasoning and an important prerequisite for mathematical reasoning (Kyttälä & Lehto, 2008). Working memory (WM), the ability to temporarily store and simultaneously manipulate information, is also considered to be a crucial cognitive factor in mathematical achievement. Research shows that both visual-spatial and verbal WM play an important role in mathematical development (Friso-Van Den Bos et al., 2013; Peng et al., 2016).

Regarding the motivational factors, expectancy-value theory posits that students' motivation is jointly determined by their expectancy for success and by the values and costs they associate with engaging in the task (Eccles & Wigfield, 2020). In this study, students' expectancy for success is conceptualised as their perceived competence in mathematics. For task value, this study focuses on intrinsic or interest value, i.e., the degree to which students value mathematics as an interesting and enjoyable activity for its own sake. Previous studies have shown that perceived competence (and related constructs such as self-efficacy and self-concept) and interest (and related constructs such as intrinsic motivation) are positively related to students' achievement (Eccles & Wigfield, 2020; Garon-Carrier et al., 2016; Huang, 2011; Renninger et al., 2015; Valentine et al., 2004; Winberg & Palm, 2021). Besides perceived competence and interest, this study examines mathematics anxiety, referring to feelings of tension, worry, and fear in mathematics-related situations (Dowker et al., 2016). Although mathematics anxiety might be classified as an affective rather than motivational variable, we consider it to be highly relevant for the domain of mathematics: Mathematics anxiety is among the most frequently researched emotions in this domain, and has been shown to be negatively related to mathematics achievement (Barroso et al., 2021; Carey et al., 2016; Namkung et al., 2019; Pekrun et al., 2017).

The positive associations between these cognitive and motivational factors on the one hand and mathematics achievement on the other may suggest that students who achieve highly in mathematics generally score relatively highly on these characteristics compared to average-achieving or low-achieving students. Although research about the cognitive characteristics of high-achieving students is relatively scarce, the available studies suggest that high-achieving students do indeed score higher on measures of fluid intelligence and WM, compared to average-achieving students (Bakker et al., 2022; Myers et al., 2017). Research about the motivational characteristics of high-achieving students is very scarce and does not focus on the specific characteristics described above. However, there are some indications that constructs related to interest, such as intrinsic motivation and need for cognition, play a role in high mathematics achievement (Bakker et al., 2022; Myers et al., 2017; Preckel et al., 2020).

1.2. *Potential differences between high-achieving students*

The research described so far used a variable-centred approach, which focuses on relations between variables which are assumed to apply to all individuals. While this type of research has provided indications about cognitive and motivational characteristics on which high-achieving students, on average, score highly, this does not imply that all high-achieving students possess all of these characteristics to an equal extent. First, the right tail of the normal distribution of abilities and achievement encompasses students with moderately above-average abilities and achievement as well as students with exceptionally high abilities and achievement. Thus, there may be substantial differences *within* this group regarding mathematics achievement as well as its cognitive and motivational correlates (Myers et al., 2017). Second and related to this, students who are proficient in some component skills of mathematics are not necessarily proficient in all of its component skills (Gilmore, 2023). For example, the practice-oriented literature describes that some high-achieving or gifted students experience relative weaknesses in the memorisation of basic arithmetic facts (Sjoers, 2015). Third, there may be various pathways to high mathematics achievement. For some students, high achievement may largely be the result of high cognitive capacities, whereas other students might have average cognitive capacities but nevertheless achieve highly as a result of a strong motivation and associated positive learning behaviours. Indeed, some case studies of mathematical prodigies have indicated that their exceptional skills seemed to be the result of intense motivation and practice, rather than exceptional cognitive abilities (Myers et al., 2017). Summing up, there may be substantial heterogeneity within the group of high-achieving students both in the degree and in the constellation of the described cognitive and motivational factors and mathematics achievement.

Such patterns of individual differences can be identified using a person-centred approach. In contrast to the variable-centred approach that focuses on the relations between variables, the person-centred approach examines how variables combine at the level of the individual, enabling the identification of subgroups with characteristic response patterns (profiles) (Hickendorff et al., 2018). This approach is particularly suitable in situations where there is (unobserved) heterogeneity and an 'average' pattern is therefore not an adequate description (Hickendorff et al., 2018), as is possibly the case for high achievement in mathematics (Gilmore, 2023; Myers et al., 2017; Preckel et al., 2020). That is, multiple cognitive and motivational factors are involved, and these factors are related in complex ways, including interactions (e.g., the effect of mathematics anxiety on achievement depends on students' working memory level; Ramirez et al., 2013). In addition, recent insights suggest that several of these cognitive and motivational factors are reciprocally related to achievement (De Smedt, 2022; Pekrun et al., 2017; Peng & Kievit, 2020). Therefore, it is relevant to examine how these variables co-occur within individuals to identify profiles of students with varying characteristics.

Differences between the resulting profiles may be quantitative and qualitative. In the case of quantitative differences, the profiles are characterised by consistently low, average, or high scores across all variables (i.e., between-student differences in level). Qualitative differences may occur within and between profiles. A profile may be characterised by a pattern of relative strengths and weaknesses (e.g., high achievement but low cognition), showing qualitative differences *within* students. If such patterns of relative strengths and weaknesses differ between profiles (e.g., one profile with high motivation but low cognition and another profile with low motivation but high cognition, implying that the profile lines are no longer parallel), they represent qualitative differences *between* students. Both quantitative and qualitative differences between students may have consequences for students' educational needs. For students with moderately high scores on all variables, frequently used within-class differentiation practices such as compacting and enrichment as provided by the mathematics curriculum

(Prast & Hickendorff, 2023) may be sufficient to meet their educational needs, whereas students who score very highly on all variables may need more rigorous adaptations such as advanced pull-out classes to be sufficiently challenged (Rogers, 2007). In case of qualitative differences, students' educational needs may also be qualitatively different: for example, students with high cognitive capacities but low motivation may need a different type of support from the teacher than students with average cognitive capacities but high motivation. Indeed, it has been suggested in the practice-oriented literature that there are different subtypes of high-achieving students, with different educational needs. For example, Sjoers (2018; inspired by Reed, 2004; Sowell et al., 1990) makes a distinction between good, fast, and creative mathematics learners, and describes how the educational needs of these subgroups differ. However, the proposed subtypes are not based on empirical findings.

1.3. Previous person-centred studies

As far as we know, no previous studies have used a person-centred approach to identify differences *between* high-achieving students. However, some studies have used a person-centred approach to identify profiles of students in mixed-achievement samples (i.e., not limited to high-achievers) based on various combinations of cognitive and motivational characteristics and mathematics achievement.

Bakker et al. (2022) investigated profiles of early primary school students based on a range of basic mathematical processes and component skills. They identified four profiles that mainly differed quantitatively from each other, i.e., reflecting consistently low, below-average, above-average and high levels across the investigated numerical abilities. Profile membership was related to students' mathematics achievement and visual-spatial, but not verbal, working memory.

Lazarides et al. (2018) and Ruelmann et al. (2021) investigated profiles based on primary school students' achievement, interest, and self-concept in mathematics. Both studies found two profiles with consistently low or high scores on all variables, reflecting quantitative differences. In addition, both studies identified two profiles with inconsistencies between motivational characteristics and achievement: "interested but hardly confident" and "hardly interested but competent" in Lazarides et al. (2018), and "motivated" (relatively high interest compared to achievement) and "unmotivated" (relatively low self-efficacy and interest despite medium achievement) in Ruelmann et al. (2021). These inconsistencies reflect qualitative differences within and between students.

Studies with secondary students, in which profiles were based on motivational characteristics only, have also revealed a combination of quantitative and qualitative differences (Lazarides et al., 2019, 2022). To the best of our knowledge there are no previous studies in which profiles were estimated based on cognitive, motivational, and achievement characteristics simultaneously.

1.4. Current study

This study investigates whether profiles of high-achieving students can be identified based on a range of cognitive characteristics (nonverbal intelligence, verbal and visual-spatial working memory), motivational characteristics (mathematics-specific perceived competence, interest and anxiety), and mathematics achievement (general mathematics achievement and arithmetic fluency). Based on the literature reviewed above (Lazarides et al., 2018; Ruelmann et al., 2021), we hypothesise that a latent profile analysis (LPA) will yield quantitative differences regarding the level of scores across all variables, as well as qualitative differences indicated by patterns of relative strengths and weaknesses within and between students. These qualitative differences may concern inconsistencies between the domains of cognition, motivation and achievement (e.g., high achievement but low interest; similar to Lazarides et al., 2018) and within these domains (e.g., relatively low arithmetic fluency compared to general mathematics achievement; (Sjoers, 2015). Although we expect to find various profiles, we have no specific expectations on the number and exact constellation of these profiles.

Furthermore, we explore whether the profiles are similar or different across grade levels (from Grade 3 through Grade 6), since all factors involved in our study show age-related developments and have complex dynamic interactions (see Section 1.1). While mathematics achievement and cognitive abilities increase over the course of primary school, motivational factors show different change trajectories: that is, perceived competence and interest generally show a decreasing trend, whereas anxiety seems to increase with age (Dowker et al., 2016; Jacobs et al., 2002; Orth et al., 2020). Based on these age-related developments, we argue that differences between grades regarding the constellation or frequency of the profiles are plausible. However, given the exploratory nature of the study and the limited previous literature, we do not make specific predictions about the direction of such potential differences between grades.

Finally, we examine whether profile membership is related to students' gender. Previous variable-centred studies have shown that, in mathematics, girls' motivation and sometimes achievement tend to be lower compared to boys (Dowker et al., 2016; Mullis et al., 2020; Preckel et al., 2008; Skaalvik & Skaalvik, 2004). Moreover, such gender differences may be more pronounced for gifted students compared to average students (Preckel et al., 2008), which might imply that these differences are especially relevant for high-achieving students in mathematics (given the overlap between non-verbal reasoning ability and mathematics achievement). Furthermore, person-centred studies in general primary school samples have provided indications that girls are overrepresented in profiles with less favourable motivational characteristics (Lazarides et al., 2018; Ruelmann et al., 2021). Therefore, we hypothesise that, if we find profiles characterised by less favourable motivational characteristics (i.e., lower perceived competence and interest, higher anxiety), girls may be overrepresented in these profiles.

2. Method

The present study involves a selection of data from the existing data set of the large-scale project GROW (Prast et al., 2018a). The original study was approved by the Ethics Committee of the Social and Behavioural Sciences Faculty, Utrecht University.

2.1. Participants

We selected students from the large dataset based on their grade level (Grades 3 through 6 in the first year of the GROW study; $N = 3497$; we will refer to this sample as 'the full mixed-achievement sample') and subsequently on achievement level (score above the 80th percentile of a nationally-representative norm group on a standardised national curriculum-based mathematics test, see also Section 2.3.1; $N = 625$). Thus, the selected sample for the current analyses consisted of 625 students from Grades 3–6 (61.4 % male), nested in 125 classes from 31 schools. Mean age at the beginning of the study was 9.7 years ($SD = 1.2$ years).

2.2. Measures

2.2.1. General cognitive skills

2.2.1.1. Intelligence. The Raven Standard Progressive Matrices (SPM; Raven et al., 1996) was used to measure non-verbal intelligence. The Raven SPM consists of five series (A to E) of 12 diagrams or designs with one part missing. Students are asked to select the correct part to complete the designs from six (series A and B) or eight (series C to E) parts. Students choose between answer options printed beneath each design to indicate which of the options logically completes the design. The difficulty of the items increases progressively. Answers are scored as incorrect (0) or correct (1). The minimum score is 0 and maximum score is 60. Internal consistency was α = .92 in the full mixed-achievement sample. Previous analyses of the entire dataset (Prast et al., 2018a) demonstrated that scores on the Raven SPM significantly predict the level of mathematics achievement ($\beta = .20$, $p < .001$).

2.2.1.2. Visual-spatial and verbal working memory. Students completed two online computerised WM tasks suitable for self-administration in the classroom, the Lion game (Van de Weijer-Bergsma et al., 2015a) and the Monkey game (Van de Weijer-Bergsma et al., 2016). The Lion game is a visual-spatial complex span task, in which students remember the location of coloured lions. In each trial, eight lions of different colours (red, blue, green, yellow, purple) are presented sequentially for 2000 milliseconds at different locations in a 4 × 4 matrix containing 16 bushes. Students are asked to remember at which location the last lion of a certain colour (e.g., red) appeared. The difficulty level of the task rises by increasing the number of colours – and therefore locations – students have to remember (ranging from one to five colours in level 1 to level 5 respectively).

The Monkey game is a backward verbal span task, in which students hear spoken one-syllable words (Van de Weijer-Bergsma et al., 2016). Students have to remember series of words and click on these words in reverse order in a 3 × 3 matrix. The difficulty level of the task rises by increasing the number of words students have to remember (ranging from two to six words in level 1 to level 5 respectively).

Both tasks consist of 20 items in total (four items per level) with no cut-off rules applied. We scored the proportion of items recalled correctly. The Lion and Monkey games respectively have excellent (Cronbach's α between .86 and .90 for different ages) and good internal consistency (Cronbach's α between .78 and .89 for different ages), and good concurrent and predictive validity (Van de Weijer-Bergsma et al., 2015a, 2016). Test-retest reliability ($\rho = .71$) for the Lion game is satisfactory. The Monkey game shows substantial stability over a period of two years.

2.3. Mathematics achievement

2.3.1. General mathematics achievement

The curriculum-based Cito mathematics tests are used to monitor the progress of mathematics achievement in most Dutch primary schools (Janssen et al., 2010). There are two assessments per grade: one at the middle and one at the end of the school year. Each test mainly contains a mixture of contextual and numerical mathematics problems that cover at least five main domains: (a) numbers and number relations, (b) addition and subtraction, (c) multiplication and division, (d) combinations of arithmetic operations, and (e) measuring (e.g., weight and length). From Grades 2 through 6, several domains are integrated in the mathematics tests successively: (f) computational estimation, (g) time, (h) money, (i) proportions, (j) fractions and (k) percentages. The difficulty level of the items for each domain increases with grade level. Raw test scores are converted to one common underlying competence scale that covers all grades using IRT, enabling the comparison of results of different tests on the same scale (Janssen et al., 2010). Competence scores can vary between 0 (lowest in Grade 1) and 169 (highest in Grade 6). Representative national norms are available, which we used to select the 20 % highest achieving students within each grade. The reliability for the mathematics tests in different grades ranges from .91 to .97 (Janssen et al., 2010).

2.3.2. Arithmetic fluency

The Arithmetic Tempo Test (De Vos, 1992) is a standardised speeded paper-and-pencil arithmetic test to measure arithmetic fluency, which is frequently used in Dutch and Flemish education. The test consists of five sets of 40 addition, subtraction, multiplication, division, and mixed problems. For each set, students have 1 minute to solve as many problems as possible. All problems consist of two-operand equations with an outcome smaller than 100 and both operands ranging between 0 and 90. The psychometric properties of the test have been established in a sample of 10,059 Flemish students (Ghesquière & Ruijssenaars, 1994). Previous analyses of the entire GROW project sample showed that four-month test-retest reliability ρ ranged between .84 and .87 (Van de Weijer-Bergsma et al., 2015b). Furthermore, a moderate to strong correlation with performance on the general mathematics achievement test was found, after controlling for grade (partial ρ between .50 and .51). The total number of problems answered correctly was scored.

2.4. Motivation for mathematics: perceived competence, interest and anxiety

The Mathematics Motivation Questionnaire for Children (MMCQ; Prast et al., 2012; Prast et al., 2018b) is a self-report questionnaire designed to measure several aspects of motivation and affect for mathematics in primary school students. The questionnaire originally included separate subscales for self-efficacy (e.g., "Do you think you will answer the math problems correctly this week?") and self-concept (e.g., "Are you good at math?"). Since these items loaded on the same factor, and since these two constructs have also been shown to be empirically indistinguishable in other studies despite subtle theoretical differences (Anderman, 2020; Eccles & Wigfield, 2020; Marsh et al., 2019; Prast et al., 2018b), the items for both subscales were combined into a twelve-item subscale for perceived competence. For interest, five items about intrinsic or interest value were selected from a task value subscale: e.g., "Do you like math?". The remaining two items measured personal value and utility value and were therefore not included in the current study. Anxiety was assessed with 5 items concerning anxious thoughts and feelings during the mathematics lesson, e.g., "During math class, are you afraid of making mistakes?"

All items were rated on the following four-point scale: 1 = NO! (strongly disagree), 2 = no (disagree), 3 = yes (agree), 4 = YES! (strongly agree). Negatively worded items were score-reversed. Internal consistency of the scales was good to excellent (Cronbach's α ranges between .92 and .93 for perceived competence and interest, and between .79 and .87 for anxiety) in the full mixed-achievement sample. A three-factor confirmatory model had good fit to the data (see Appendix 1). Test-retest reliability for the complete MMQC over a 1-week period was good (r ranges from .82 to .93 for the various scales; Prast et al., 2018b). A mean for each scale was calculated, ranging from 1 to 4 with a higher score reflecting higher perceived competence, interest, or anxiety.

2.5. Procedure

The data were collected at three occasions, in May/June 2012 (T1), September/October 2012 (T2) and January/February 2013 (T3). At T1, general mathematics achievement was assessed by the classroom teacher as part of the standard student monitoring procedure with the Cito mathematics test. At T2, intelligence, visual-spatial WM and motivation were assessed. A paper-and-pencil version of the Raven SPM was group-administered in class by research assistants. Assessment was ended after 60 min. For the visual-spatial WM assessment, teachers received an email containing login information for their class and were asked to let all students complete the task within a period of three weeks. Motivation was group-administered in class with a paper-and-pencil questionnaire. In Grade 3, a research assistant read each question aloud, after which the students wrote down their answer. In Grades 4 through 6, students completed the questionnaire independently after receiving instructions from a research assistant. At T3, we assessed arithmetic fluency and verbal WM. Again, teachers received login information for the assessment of Verbal WM. The fluency test was administered by the teacher.

2.6. Missing data

From the 625 students in the sample (see Table 1 for sample characteristics), data were missing for $n = 46$ students (7.4 %) on arithmetic fluency, for $n = 82$ (13.1 %) on verbal WM, for $n = 52$ (8.3 %) on visual-spatial WM, and for $n = 24$ (3.8 %) on intelligence. With regard to motivation, $n = 33$ students (5.3 %) had missing data for interest, $n = 39$ (6.3 %) for perceived competence, and $n = 32$ (5.1 %) for anxiety. In total, $n = 428$ (68.5 %) students had complete data on all variables. The large scale of the GROW study made it unfeasible to keep track of reasons for missingness. However, we expect that the reasons for missing data were mainly due to the absence of students from school (e.g., due to sickness, dentist visit, attendance to an official family event). Thus, it would be plausible to assume the missing data mechanism is missing at random (Schafer & Graham, 2002). We used Full Information Maximum Likelihood (FIML) to handle missingness in the latent profile analyses, making imputation unnecessary.

2.7. Data analysis

To investigate whether there are quantitative and qualitative differences between high-achieving students on a range of cognitive, motivational, and achievement variables, we used Latent Profile Analysis (LPA; e.g., Hickendorff et al., 2018). This person-centred approach aims to identify latent (hidden) subgroups (clusters) of students who share a characteristic response pattern or profile across the observed variables. In the current analysis we used eight observed variables: students' scores on the two mathematics measures (general mathematics achievement and arithmetic fluency), the three general cognitive variables (nonverbal intelligence, visual-spatial WM, and verbal WM), and the three motivational variables (interest, perceived competence, and anxiety). Raw scores were standardised within each grade, based on the mean and standard deviation in the full mixed-achievement sample, before entering the LPAs, to create a common frame of reference for all variables and across the four grades. We first conducted separate LPAs for each grade. Next, we evaluated whether the number and constellation of the profiles were similar enough to justify one overall LPA across grades.

LPAs yield two sets of model parameters: (a) cluster probabilities, reflecting the prevalence of each profile; (b) per cluster, the estimated mean and variance for each variable, characterising the profile. The LPAs were conducted using Latent Gold 6.0 (Vermunt & Magidson, 2021). For each grade, we ran LPA models with an increasing number of profiles to select the optimal number of profiles, based on model-fit statistics such as the CAIC and BIC (Nylund-Gibson & Choi, 2018). Including a multilevel effect to account for the nested data structure (i.e., students nested into classrooms) did not improve the model fit and was therefore discarded in the further analyses.

To investigate whether high-achieving boys and girls differed in their likelihood to belong to each of the profiles, gender was included as a covariate. To correct for the classification error that is inherent to assigning students to profiles, we used a bias-adjusted three-step approach (Bakk et al., 2013).

Table 1
Raw score means and standard deviations (between brackets) of all variables, and one-way ANOVA test of grade differences.

Variable	Grade 3	Grade 4	Grade 5	Grade 6	One-way ANOVA
Math achievement	84.3 (8.41)	98.1 (5.85)	107.7 (6.98)	122.4 (6.21)	$F(3,621) = 787.8$; $p < .001$; $\eta^2 = .792$
Fluency	88.1 (19.49)	105.3 (21.96)	122.1 (23.03)	141.8 (22.66)	$F(3,575) = 155.4$; $p < .001$; $\eta^2 = .448$
Intelligence	40.4 (6.38)	44.7 (4.87)	46.8 (4.88)	48.6 (4.03)	$F(3,597) = 71.6$; $p < .001$; $\eta^2 = .265$
Visual-spatial WM	0.72 (0.138)	0.78 (0.108)	0.79 (0.106)	0.79 (0.111)	$F(3,569) = 15.1$; $p < .001$; $\eta^2 = .074$
Verbal WM	0.58 (0.107)	0.63 (0.111)	0.64 (0.113)	0.68 (0.102)	$F(3,539) = 18.0$; $p < .001$; $\eta^2 = .091$
Interest	3.23 (0.836)	3.04 (0.797)	2.87 (0.801)	2.89 (0.769)	$F(3,588) = 7.0$; $p < .001$; $\eta^2 = .034$
Perceived competence	3.58 (0.368)	3.42 (0.407)	3.42 (0.420)	3.46 (0.378)	$F(3,582) = 6.4$; $p < .001$; $\eta^2 = .064$
Anxiety	1.31 (0.469)	1.47 (0.487)	1.42 (0.465)	1.45 (0.476)	$F(3,589) = 3.6$; $p = .014$; $\eta^2 = .018$

3. Results

3.1. Descriptives

Table 1 shows the means and standard deviations of the raw scores on all variables in the current sample of 20 % highest achieving students per grade. On all mathematics achievement measures and general cognitive variables, students in higher grades had higher means (although not all pairwise differences were significant). For the motivational variables, interest decreased with grade (significant differences between Grade 3 versus Grade 5 and 6) as did perceived competence (significant differences between Grade 3 versus Grades 4 and 5). Anxiety showed a small increase across grades (significant differences between Grade 3 and Grade 4).

Before conducting the main analyses, we assessed how these scores in our selected sample related to the full mixed-achievement sample by examining the mean sample-standardised scores on all variables. On average, the high-achieving students scored 1.3 standard deviation higher than average on general mathematics achievement, the selection criterion. They scored approximately 0.7 standard deviation higher than average on fluency, intelligence, and perceived competence, approximately 0.5 standard deviation higher than average on verbal WM, 0.4 standard deviation lower on anxiety, and 0.3 standard deviation higher on visual-spatial WM and interest. For each measure except mathematics achievement (our selection criterion), the range from the lowest to the highest z-score within each grade spanned at least three standard deviations. For example, for fluency, the z-scores in Grade 6 ranged between −1.78 and 2.60, indicating that some high-achieving students scored almost two standard deviations below the average of students in their grade in the full mixed-achievement sample, whereas others scored more than two standard deviations above the full-sample average. For mathematics achievement it spanned at least two standard deviations, from $z = 0.70$ (our cut-off criterion) to at least $z = 2.70$ (in Grade 6, with higher values in the other grades).

3.2. Latent profile analysis

To investigate whether there are quantitative and qualitative differences between high-achieving students across the variables, we estimated latent profile models per grade. Fit statistics of models with 1–6 clusters are presented in Tables 2–5. The best fitting models had different numbers of profiles per grade, with two profiles in grade 4, three profiles in grade 3 and 6, and four profiles in grade 5. Reviewing the two-, three-, and four-cluster solutions showed that even with the same number of clusters, the resulting profiles were dissimilar (e.g., the

Table 2
Model fit statistics for Latent Profile Analysis Grade 3 (n = 178).

# profiles	LL	#par	BIC	CAIC	ICL-BIC	Class. error	Entropy R^2	BLRT (df = 17)	p
1	−1483.3	16	3049.6	3065.6	3049.6				
2	−1333.1	33	2837.1	2870.1	2886.7	.056	.798	300.57	<.001
3	−1234.1	50	**2727.2**	**2777.2**	**2795.6**	.076	.822	198.00	<.001
4	−1198.0	67	2743.1	2810.1	2841.8	.103	.799	72.20	<.001
5	−1158.4	84	2752.0	2836.0	2845.6	.095	.832	79.18	<.001
6	−1103.5	101	2730.5	2874.3	2797.8	.075	.888	109.63	.002

Note. LL = log likelihood, #par = number of parameters, BLRT = Bootstrap Likelihood Ratio Test. Lowest value of BIC, CAIC and ICL-BIC in boldface.

Table 3
Model fit statistics for Latent Profile Analysis Grade 4 (n = 152).

# profiles	LL	#par	BIC	CAIC	ICL-BIC	Class. error	Entropy R^2	BLRT (df = 17)	p
1	−1250.7	16	2581.8	2597.8	**2581.8**				
2	−1185.1	33	**2535.9**	**2568.9**	2592.3	.071	.732	131,33	<.001
3	−1149.1	50	2549.4	2599.4	2620.3	.095	.764	71,92	<.001
4	−1115.4	67	2567.3	2634.3	2645.7	.103	.802	67,50	<.001
5	−1080.2	84	2582.4	2666.4	2668.1	.103	.816	70,34	<.001
6	−1056.4	101	2624.0	2721.2	2702.4	.098	.838	47,55	.014

Note. LL = log likelihood, #par = number of parameters, BLRT = Bootstrap Likelihood Ratio Test. Lowest value of BIC, CAIC and ICL-BIC in boldface.

Table 4
Model fit statistics for Latent Profile Analysis Grade 5 (n = 167).

# profiles	LL	#par	BIC	CAIC	ICL-BIC	Class. error	Entropy R^2	BLRT (df = 17)	p
1	−1479.6	16	3041.1	3057.1	3041.1				
2	−1362.6	33	2894.1	2927.1	2949.0	.076	.762	234.01	<.001
3	−1317.8	50	2891.6	2941.6	2989.5	.122	.728	89.52	<.001
4	−1251.9	67	**2846.8**	**2913.8**	**2931.4**	.099	.815	131.80	<.001
5	−1219.7	84	2869.2	2953.2	2955.2	.099	.837	64.57	<.001
6	−1182.9	101	2882.6	2983.3	2968.7	.097	.853	73.58	<.001

Note. LL = log likelihood, #par = number of parameters, BLRT = Bootstrap Likelihood Ratio Test. Lowest value of BIC, CAIC and ICL-BIC in boldface.

Table 5
Model fit statistics for Latent Profile Analysis Grade 6 (n = 128).

# profiles	LL	#par	BIC	CAIC	ICL-BIC	Class. error	Entropy R^2	BLRT (df = 17)	p
1	−1066.2	16	2209.9	2225.9	2209.9				
2	−990.9	33	2141.8	2174.8	2171.2	.050	.832	150.58	<.001
3	−931.8	50	**2106.2**	**2156.2**	**2160.7**	.088	.805	118.16	<.001
4	−895.6	67	2116.3	2183.3	2167.6	.072	.853	72.34	<.001
5	−868.6	84	2144.7	2228.7	2196.7	.071	.872	54.08	.004
6	−841.8	101	2173.7	2274.7	2222.2	.068	.888	53.51	.002

Note. LL = log likelihood, #par = number of parameters, BLRT = Bootstrap Likelihood Ratio Test. Lowest value of BIC, CAIC and ICL-BIC in boldface.

three-cluster solution in grade 3 yielded different profiles than the three-cluster solution in grade 4–6). Therefore, already at this point in the analyses we concluded that one overall LPA for the four grades simultaneously was not feasible.

In interpreting the solutions, we first evaluated whether the profiles were parallel (reflecting quantitative differences between students) or not (qualitative differences between students). To ease this evaluation, we transposed the variable mathematics anxiety in the profile graphs, so that higher means indicate lower sample-standardised anxiety. Next, we zoomed in on the qualitative differences within profiles (i.e., inconsistencies between variables reflecting within-student patterns of relative strengths and weaknesses) and between profiles (i.e., between-student differences in these patterns). In order to interpret profiles in a similar way across the grades, we used the following 'universal' thresholds for the estimated values. Within this high-achieving sample, we classified standardised means below 0.5 as 'relatively low' (notwithstanding that these scores are average compared to the full mixed-achievement sample); between 0.5 and 1.0 as 'moderate', between 1.0 and 1.5 as 'high' and above 1.5 as 'very high'. We then formulated profile labels that described the most distinguishing characteristics of each profile (see Appendix 3 for a more elaborate justification). Appendix 2 presents the estimated means and variances for the selected models.

In Grade 3, BIC, CAIC and ICL-BIC suggested a model with three profiles (Table 2; classification error 0.076; R^2 entropy .822). Entropy values above .80 indicate good classification of individuals into profile clusters (Nylund-Gibson & Choi, 2018). All but one variable (visual-spatial WM) contributed significantly to the profile differences. Fig. 1 shows the profiles (i.e., the cluster-specific means). Since there were clear deviations from parallelism of the profiles, most obvious on the motivational variables, there were qualitative differences between the students.

The blue profile (43 % of the students) scored relatively low on all variables. Only general achievement was in the high range (in line with our selection criterion), although it was lower than that of the other profiles. Therefore, we labelled this profile 'relatively low on all variables'. The yellow profile (28 %) displayed high general achievement and fluency, relatively low WM and moderate intelligence, and moderate to high motivation. We labelled this profile 'motivated'. The orange profile (29 %) was characterised by inconsistent achievement (very

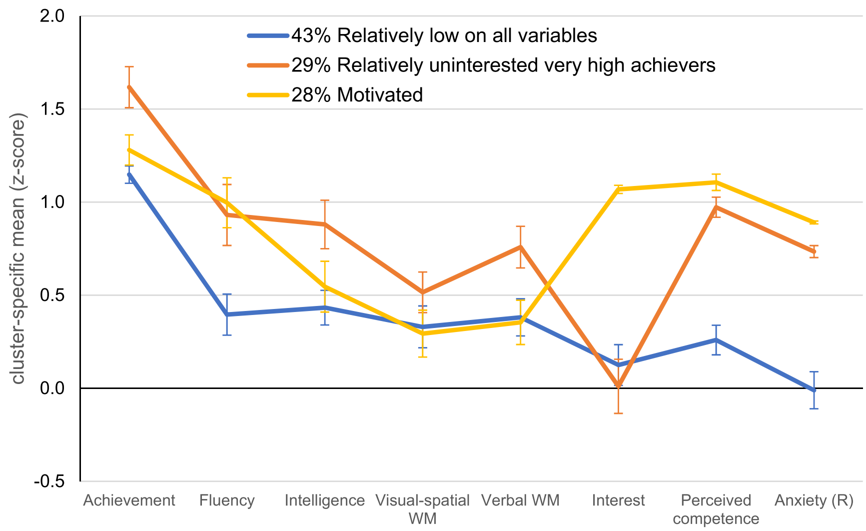

Fig. 1. Profiles of cluster-specific means (with error bars); three-cluster solution Grade 3.

high general achievement vs. moderate fluency), moderate cognition and inconsistent motivation: interest was relatively low, whereas perceived competence and anxiety were moderate. Especially the relatively low level of interest was striking. Therefore, we labelled the orange profile 'relatively uninterested very high achievers'.

In Grade 4, although the ICL-BIC suggested one profile, both BIC and CAIC suggested a model with two profiles (Table 3 and Fig. 2); classification error = 0.071 and R^2 entropy = .732. Intelligence, verbal WM, visual-spatial WM, and fluency did not differentiate significantly between the profiles, the other variables did. Again, the profiles were not parallel, implying qualitative differences between the students. Both profiles displayed inconsistent achievement (high general achievement versus moderate fluency), although the green profile scored somewhat higher on general achievement. The scores for the cognitive variables were moderate to relatively low for both profiles, with largely parallel lines. However, the profiles clearly deviated on motivation: the green profile scored relatively low on all motivational variables, whereas the orange profile was characterised by moderate motivation. Note the difference of more than one standard deviation in (the absence of) anxiety. We therefore labelled the green profile (48 % of the students) 'relatively unmotivated' and the orange profile (52 %) 'moderately motivated'.

In Grade 5, BIC, CAIC, and ICL-BIC suggested a model with four profiles (Table 4 and Fig. 3); classification error = 0.099 and R^2 entropy = .815. All variables contributed significantly to the profiles and again, the profiles were not parallel. The blue profile (22 % of the students) scored relatively low on all variables except general achievement (which was moderate, but lower than that of the other profiles). We therefore labelled this profile 'relatively low on all variables'. The purple profile (31 % of the students) was characterised by inconsistent achievement (general achievement almost one standard deviation higher than relatively low fluency), moderate cognition, and relatively low motivation. We labelled this profile 'relatively unmotivated with relatively low fluency'. The most obvious difference between these profiles and the two remaining profiles was the level of motivation, which was much higher for both the yellow profile (20 % of the students) and the orange profile (27 % of the students). The yellow profile was characterised by inconsistent achievement (very high general achievement, moderate fluency), inconsistent cognition (moderate intelligence and verbal working memory, relatively low visual-spatial working memory), and moderate to high motivation. We labelled this profile 'motivated'. The orange profile displayed high general achievement and fluency,

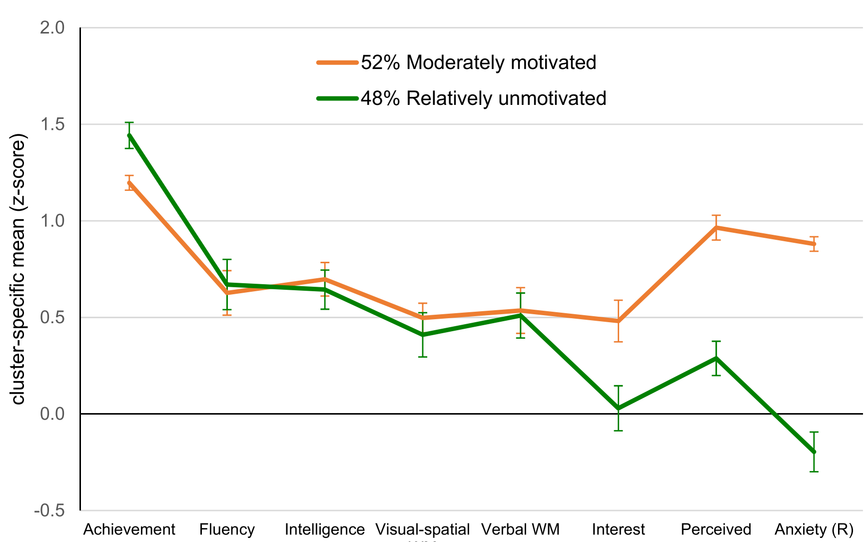

Fig. 2. Profiles of cluster-specific means (with error bars); two-cluster solution Grade 4.

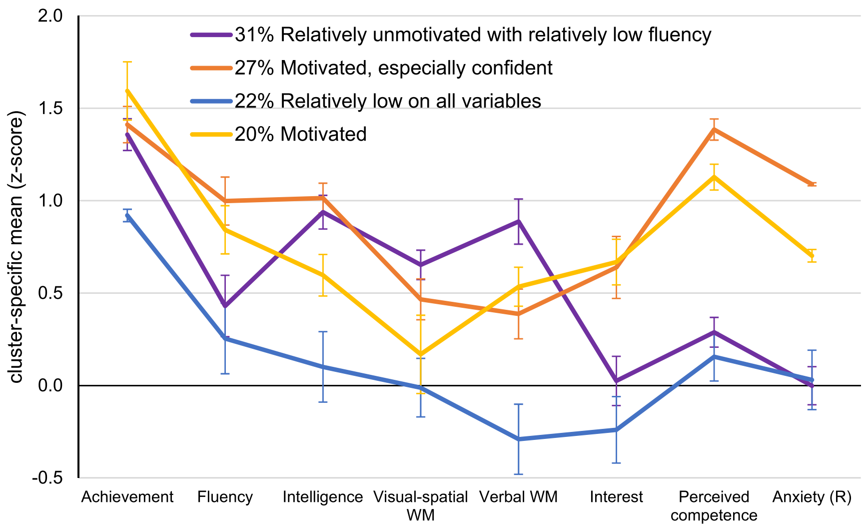

Fig. 3. Profiles of cluster-specific means (with error bars); four-cluster solution Grade 5.

inconsistent cognition (moderate to high intelligence, relatively low WM), and moderate to high motivation. While the yellow and orange profile shared a similar moderate level of interest, the orange profile scored even higher on perceived competence and (absence of) anxiety. We therefore labelled this profile 'motivated, especially confident'.

Finally, in Grade 6, BIC, CAIC, and ICL-BIC suggested a model with three profiles (Table 5 and Fig. 4); classification error = 0.088 and R^2 entropy = .805. All variables except the two WM measures contributed significantly to the differences between the profiles and the profiles were not parallel. The blue profile (37 % of the students) scored relatively low on almost all variables except general achievement, although intelligence was just above the borderline with moderate. To be consistent with the name of similar profiles in different grades, we labelled this profile 'relatively low on all variables'. The grey profile (37 % of the students) was characterised by very high general achievement and moderate fluency, inconsistent cognition (with relatively low visual-spatial WM and moderate intelligence and verbal WM), and motivation in the moderate to relatively low range. We labelled this profile 'moderately motivated very high achievers'. The orange profile (27 % of the students) displayed high general achievement and fluency, inconsistent cognition (moderate intelligence, relatively low visual-spatial WM, borderline low-to-moderate verbal WM), and moderate to very high motivation, with very high perceived competence as a distinctive feature. We therefore labelled this profile 'motivated, especially confident'.

Finally, we examined the percentage of variance of each of the variables that is explained by the profiles, in each of the selected latent profile models (Fig. 5). Anxiety and perceived competence explained the

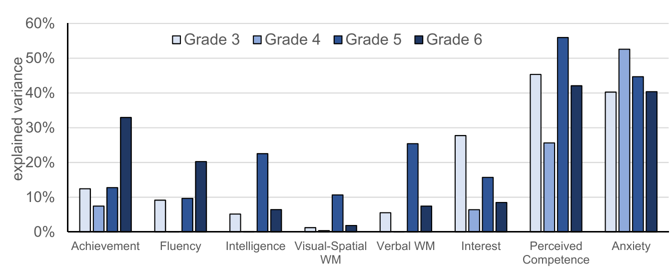

Fig. 5. Percentage of explained variance per variable in selected latent profile model.

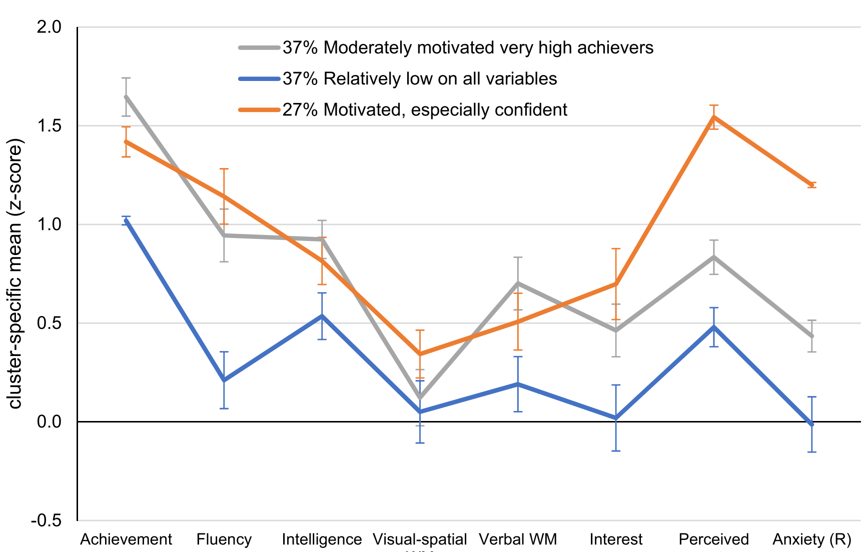

Fig. 4. Profiles of cluster-specific means (with error bars); three-cluster solution Grade 6.

highest percentage of variance in each grade, and thus contributed most (and most consistently) to the unobserved heterogeneity in high-achieving students. The extent to which the other variables differentiated between the profiles differed between grades.

3.3. Gender differences

For each grade, we tested whether boys and girls differed in the likelihood to belong to each of the profiles from the selected model, using a bias-adjusted three-step approach. In Grade 3, overall gender differences were significant, Wald(3) = 6.797, $p = .033$. Post-hoc analyses showed that girls (57 %) were significantly more likely than boys (35 %; $z = 2.61$) to belong to the 'relatively low on all variables' profile. Boys and girls were equally likely to belong to the 'relatively uninterested very high achievers' profile (boys 34 %; girls 21 %, $z = 1.26$) and the 'motivated' profile (boys 32 %; girls 22 %; $z = 1.02$). Gender differences were not significant in Grade 4, Wald(2) = 0.049, $p = .82$, Grade 5, Wald(4) = 4.600, $p = .20$, and Grade 6, Wald(3) = 4.966, $p = .083$.

4. Discussion

Most previous research on high-achieving students is variable-centred and shows that strong cognition and motivation are related to high mathematics achievement. Practice-oriented literature suggests however that there are different subtypes of high-achieving students, with different educational needs. In this study, we used a person-centred approach on an existing dataset to examine whether quantitatively and qualitatively different profiles of high-achieving primary school students can be identified based on a range of cognitive characteristics (nonverbal intelligence, visual-spatial memory, and verbal working memory), motivational characteristics (mathematics-specific interest, perceived competence, and anxiety), and mathematics achievement (general mathematics achievement and arithmetic fluency). Furthermore, we investigated whether profiles were similar or different across grade levels, and whether boys and girls were distributed equally across profiles. As hypothesised, several profiles could be distinguished in each grade and these profiles differed from each other both quantitatively and qualitatively.

4.1. Quantitative differences

In all grades except Grade 4, we found a 'relatively low on all variables' profile. On general mathematics achievement, these students scored at least moderate (since this was our selection criterion), but generally lower than students in the other profiles. For all other variables, students in these profiles scored around and sometimes (in Grade 5) even slightly below the average compared to the full mixed-achievement sample. These profiles with relatively low scores should be viewed in light of the rather lenient inclusion criterion (top 20 % on a standardised mathematics test): this study targeted a relatively broad group of high-achieving students, which may include but is certainly not limited to 'mathematically gifted' students with exceptional mathematical abilities or achievement (cf. Myers et al., 2017). Nevertheless, it shows that students with average cognition and motivation compared to the full mixed-achievement sample managed to achieve sufficiently highly on the general achievement test to meet our inclusion criterion. Possibly, the *combination* of around-average scores on all variables, without any severe weaknesses, enabled these students to achieve highly in mathematics. In addition, other factors than individual cognitive and motivational characteristics may also play an important role in the development of high mathematical achievement (e.g., the home and school environment; De Smedt, 2022; Gilmore, 2023; Preckel et al., 2020).

4.2. Qualitative differences

Besides differences in level, we found many inconsistencies between the variables in the profiles: such inconsistencies occurred between domains (achievement, cognition and motivation) as well as within these domains. These inconsistencies formed patterns of relative strengths and weaknesses within profiles, implying qualitative differences *within* students. Moreover, these patterns of relative strengths and weaknesses differed between profiles, implying qualitative differences *between* students. We continue to describe and interpret the most important qualitative differences.

4.2.1. Motivation

Qualitative differences within and between the profiles were often related to motivation. Inconsistencies occurred within the motivational domain as well as between the domains (motivation versus achievement and cognition). Within the motivational domain, inconsistencies mainly concerned relatively low interest compared to perceived competence (e.g., the 'relatively uninterested very high achievers' in Grade 3 and the 'motivated, especially confident' profile in Grades 5 and 6). While previous correlational studies have shown that students who feel competent in a subject generally also tend to value it more (Eccles & Wigfield, 1995), the current findings demonstrate that perceived competence and interest are not necessarily at the same high level within individual high-achieving students. Given that perceived competence tends to be a stronger predictor of achievement whereas interest tends to be a stronger predictor of achievement-related choices (Eccles & Wigfield, 1995), this might imply that students with high perceived competence but relatively low interest might be sufficiently motivated to achieve in obligatory school situations (e.g., taking a standardised test), but might be less inclined to engage in mathematics in situations where they have a choice (e.g., extracurricular activities or choosing advanced mathematics), with potential consequences for the development of their mathematical talent and their future career choices. However, this is a speculation that would need to be investigated in future research, keeping in mind that the absolute value of interest in these profiles was not low (above the midpoint of the scale and at least average compared to the full mixed-achievement sample). Since these inconsistencies between perceived competence and interest were present within some profiles but not in others, they also imply qualitative differences between students. In contrast, perceived competence tended to be somewhat higher than (absence of) anxiety, but these lines were roughly parallel for all profiles in all grades: thus, these represent qualitative differences within but not between students.

Regarding inconsistencies between domains, there were profiles with relatively low motivation compared to achievement (e.g., the 'relatively unmotivated' profile in Grade 4 and the 'relatively unmotivated with relatively low fluency' profile in Grade 5), but no profiles with overall higher motivation compared to achievement (which would have been statistically improbable, given the high achievement level of our sample). These findings resemble those of previous studies in mixed-achievement samples in which profiles with inconsistencies between various motivational variables and achievement were also reported (Lazarides et al., 2018; Ruelmann et al., 2021). Specifically, the profiles with relatively low motivation compared to achievement are similar to the "hardly interested but competent" profile found by Lazarides et al. (2018) and to the "unmotivated" profile reported by Ruelmann et al. (2021). The current study shows that such inconsistencies can also be found *within* a group of high-achieving students. At the same time, it should be noted that the exact patterns of relative strengths and weaknesses vary substantially between grade levels and samples.

4.2.2. Achievement

Inconsistencies also occurred frequently between general mathematics achievement and arithmetic fluency. For most profiles, students' fluency was somewhat lower than their general achievement. However, the extent of this difference differed between profiles. In some profiles, the difference approached one standard deviation (e.g., the 'relatively unmotivated with relatively low fluency' profile in Grade 5: $z = 1.36$ for general achievement vs. $z = 0.43$ for fluency), whereas this difference was less than half of a standard deviation in other profiles (e.g., $z = 1.41$ vs. $z = 1.00$ for the 'motivated, especially confident' profile in the same grade). Thus, the difference between general achievement and fluency is a within-student difference that occurs within many profiles, but also affects parallelism in some cases because this difference is more pronounced in some profiles than others. It should be kept in mind that, since we selected students based on their high general achievement, it was statistically much more probable that we would find profiles with relatively high general achievement compared to fluency than profiles with the opposite pattern. Nevertheless, this finding is consistent with practice-oriented literature which describes that some high-achieving students or gifted students experience weaknesses in the memorisation of basic arithmetic facts (Sjoers, 2015). The current findings suggest that such weaknesses do exist, but they are relative weaknesses (compared to high scores on other variables) and are much more pronounced for some students than for others.

4.2.3. Cognition

The cognitive variables generally contributed little to the differences between the profiles, except in Grade 5. Inconsistencies between the cognitive variables did occur and these mostly concerned relatively low WM, particularly visual-spatial WM, compared to intelligence (e.g., the 'motivated' profile in Grade 3 and in Grade 5, and all profiles in Grade 6). Thus, relatively low (visual-spatial) WM compared to other variables may represent a qualitative difference *within* several profiles. Even some of the highest-achieving profiles (e.g., the 'motivated' profile in Grade 5 and the 'moderately motivated very high achievers' in Grade 6) displayed this characteristic. Thus, although high-achieving students on average score somewhat higher than the general population on visual-spatial WM (in line with Bakker et al., 2022), high visual-spatial WM does not seem to be a necessary condition for high mathematics achievement as defined in the current study. Furthermore, cognitive characteristics did not seem to play a major role in distinguishing *between* the profiles in most grades. The inclusion of cognitive variables in the latent profiles, besides motivational and achievement variables, was an extension of previous studies (e.g., Lazarides et al., 2018; Ruelmann et al., 2021). However, the results suggest that this addition does not add much explanatory value.

4.3. Grade and gender differences

Regarding grade level, we found mean differences on all variables included in the analyses, with higher achievement and cognition, lower interest and perceived competence, and higher anxiety scores in higher grades – although not all pairwise differences were significant. These patterns were in line with previous studies (Dowker et al., 2016; Jacobs et al., 2002; Orth et al., 2020). The latent profile analyses per grade resulted in different numbers and constellations of profiles across grades. Therefore, it was not possible to examine whether students were under- or over-represented in certain profiles depending on grade level. There were no clear patterns of systematic differences from the lower to the higher grades in the number or constellation of the profiles. In each grade, perceived competence and anxiety explained a large amount of the differences between the profiles. The contribution of the other variables varied more strongly between grade levels, with relatively large contributions for interest in Grade 3, intelligence and verbal working memory in Grade 5, and achievement in Grade 6. Despite the fact that the profiles differed between grades, the quantitative and qualitative differences described above occurred in several grades and may therefore represent general patterns which may be investigated in more detail in future research.

Our high-achieving sample included relatively few girls (38.6 % girls in the high-achieving sample compared to 50.2 % girls in the full mixed-achievement sample), which is not unexpected given the small but significant gender difference in mathematics achievement in the Netherlands (Mullis et al., 2020). However, *within* this high-achieving sample, profile membership was largely similar for boys and girls. Only in Grade 3, girls were significantly more likely to belong to the 'relatively low on all variables' profile. This profile scored relatively low on most variables – including the motivational variables – compared to the other profiles, which is line with our expectation that girls would be overrepresented in profiles with less favourable motivational characteristics. In Grades 4 through 6, profile membership was not significantly related to gender. Thus, our hypothesis that there would be gender differences in profile membership, with an overrepresentation of girls in profiles with less favourable motivational characteristics, was largely rejected. These findings imply that, although girls may be underrepresented among high-achieving students in mathematics, the constellation of cognitive, motivational and achievement characteristics of high-achieving girls is mostly similar compared to high-achieving boys.

Possibly, high achievement in mathematics is a protective factor which reduces the potential negative effects of gender stereotyping on girls. For example, girls might be less prone to developing low perceived competence when it is evident that they achieve highly compared to most of their classmates, including boys. Indeed, previous work has shown that the effects of stereotype threat are moderated by several factors, including educational context (advanced versus standard mathematics) and gender identity (with complex interactions; see Casad et al., 2017). This might explain why we did not find an overrepresentation of girls in profiles with less favourable motivational characteristics, in contrast to previous studies in mixed-achievement samples (Lazarides et al., 2018; Ruelmann et al., 2021). Nevertheless, the findings are somewhat inconsistent with previous findings of more pronounced gender differences on several motivational and achievement variables (not combined in profiles) for gifted compared to non-gifted students in students of Grade 6 in Germany (Preckel et al., 2008). This difference might be explained by the different selection criterion (high nonverbal reasoning ability in the Preckel et al. (2008) study compared to high mathematics achievement in the current study) and educational context (secondary school in Germany versus primary school in the Netherlands). The current findings suggest that high-achieving girls *and* boys can be characterised by latent profiles with different motivational characteristics, and that gender does not play a major role in determining this characterisation in this context.

4.4. Limitations, conclusions, and implications

The use of an existing dataset enabled us to study many relevant variables in a large sample of high-achieving students. Nevertheless, a limitation is that we did not have the opportunity to add potentially relevant variables. In future research investigating profiles of high-achieving students in mathematics, other variables which might be particularly relevant for this population could be examined, such as need for cognition (Bakker et al., 2022; Preckel et al., 2020) or creativity (Sjoers, 2018). The motivation for including the top 20 % of highest-achieving students was more practical than theoretical: this corresponds with the highest achievement category on the Cito mathematics test and therefore these students would typically be classified and treated as high-achieving students by teachers. However, it is possible that different results would have been obtained with a different selection criterion.

Furthermore, it should be kept in mind that the current study was exploratory, and that the sample sizes for the latent profile analyses were relatively small (128–167). Replication would be necessary to investigate whether similar patterns can be found in different samples. We therefore caution readers not to over-interpret the current findings by assuming that these exact profiles would also be found in these specific grades in different samples. We do not expect that the results of this study will replicate at this very detailed level, but rather at the level of our main conclusions.

Notwithstanding these limitations, several relevant conclusions can be drawn from the current study. Our findings suggest that there is substantial variation between high-achieving students at the level of single variables, as evidenced by the broad range of z-scores on all the cognitive, motivational and achievement variables in our data set. The results of the LPAs provide insight into how these variable-level scores combine within individual students, and how these combinations differ between students. The LPAs yielded both quantitative and qualitative differences. Regarding the quantitative differences, three out of four grades had a 'relatively low on all variables' profile, indicating that there is a group of high-achieving students with generally lower scores on all variables compared to other high-achieving students.

Regarding the qualitative differences, we found inconsistencies between motivational variables (e.g., relatively low interest compared to perceived competence), between motivation and achievement (e.g., relatively low motivation compared to achievement), and between general mathematics achievement and arithmetic fluency (i.e., relatively low fluency compared to general achievement). These inconsistencies represent differences within students, but when different profiles have different patterns of inconsistencies, they also represent differences between students. The results of the LPAs show that the motivational variables played the largest role in explaining differences between the profiles. Specifically, perceived competence and anxiety consistently explained a substantial part of the variance between the profiles across all grades, whereas the explained variance of the other variables was smaller or differed more across grades.

These main findings have important implications for educational practice. In the Netherlands, many schools implement differentiation using within-class homogeneous achievement groups for mathematics (Prast & Hickendorff, 2023). Students who met the inclusion criterion for this study would typically be placed in a high achievement group and receive differentiated instruction and practice as a subgroup (e.g., curriculum compacting, enrichment exercises, less whole-class instruction). However, our findings show that there can be substantial variation within such a "homogeneous" achievement group, predominantly in the motivational variables. Teachers should be aware of these individual differences, which may contradict intuitive implicit assumptions about high-achieving students in mathematics: our findings clearly show that not all high-achieving students have very high cognitive skills (although some do); not all high-achieving students feel very competent (although some do); and not all high-achieving students are very interested in mathematics (although some are).

These individual differences imply that high-achieving students may have diverse educational needs. For example, students with relative weaknesses in arithmetic fluency may not be well served by skipping many fluency exercises, as is often a consequence of curriculum compacting. This implies that teachers should consciously evaluate whether the suggestions for curriculum compacting as provided by the mathematics curriculum are appropriate for all of their high-achieving students.

Students with different motivational characteristics may also require different types of support from the teacher: students with high perceived competence but a relatively low level of interest may need instruction or practice that sparks their interest, such as challenging creative exercises, whereas unconfident students may need a different type of instruction or feedback that allows them to feel competent. We do not suggest that teachers should attempt to classify all their high-achieving students as belonging to one of the profiles resulting from the current study and then provide differentiation accordingly. However, we think that teachers and teacher educators need to consider variations among high-achieving students. While suggestions for differentiation for high-achieving students as a subgroup within heterogeneous classes can be very useful, they should not be implemented uncritically as a one-size-fits-all treatment. Teachers should keep in mind that students within such a high-achieving group may also have diverse educational needs. More specifically, teachers could be alert to inconsistencies that repeatedly occurred in the current study, such as relatively low arithmetic fluency and relatively low (aspects of) motivation. In their daily classroom practice, teachers collect a lot of formal and informal data about their students which could enable them to notice such inconsistencies. Based on their knowledge of their students and their professional competence, teachers could then implement differentiation in a flexible way: teachers could use their curricular method's ready-made suggestions for differentiation as a starting point and make individual adaptations where necessary to attune their mathematics lessons to the diverse needs of their high-achieving students.

CRediT authorship contribution statement

Emilie J. Prast: Writing – review & editing, Writing – original draft, Methodology, Data curation, Conceptualization. **Marian Hickendorff:** Writing – review & editing, Writing – original draft, Visualization, Methodology, Formal analysis, Conceptualization. **Eva Van de Weijer-Bergsma:** Writing – review & editing, Writing – original draft, Methodology, Data curation.

Institutional review board statement

The study was approved by the Ethics Committee of the Social and Behavioural Sciences Faculty, Utrecht University (protocol code 22-0070).

Declaration of competing interest

All authors declare no conflict of interest.

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Appendix 1. Confirmatory factor analysis of the motivation questionnaire

Using lavaan (Rosseel, 2012), we fit a confirmatory model with three factors: interest (5 items), perceived competence (12 items) and anxiety (5 items) on the data of 3066 students (all students from the full mixed-achievement sample who completed the motivation questionnaire). The fit of this model was good: CFI = 0.954, RMSEA = 0.055, SRMR = 0.036. The chi-square statistic was significant ($\chi^2 = 2148.493$ ($df = 206$), $p < .001$) but that can be attributed to the large sample size. Standardised factor loadings were all above 0.600, see Table A1. There was a positive correlation between interest and perceived competence ($r = .529$, $p < .001$). Anxiety correlated negatively with interest ($r = -.298$, $p < .001$) and competence ($r = -.679$, $p < .001$).

Table A1
Factor loadings of confirmatory three-factor model.

Item	Factor loading (standardised)
Interest1	.850
Interest2	.915
Interest3	.867
Interest4	.821
Interest5	.762
PerceivedCompetence1	.694
PerceivedCompetence2	.603
PerceivedCompetence3	.603
PerceivedCompetence4	.624
PerceivedCompetence5	.609
PerceivedCompetence6	.654
PerceivedCompetence7	.816
PerceivedCompetence8	.768
PerceivedCompetence9	.830
PerceivedCompetence10	.872
PerceivedCompetence11	.748
PerceivedCompetence12	.780
Anxiety1	.778
Anxiety2	.600
Anxiety3	.799
Anxiety4	.687
Anxiety5	.790

Appendix 2. Means and variances per profile

Table A2.1
Estimated means and variances with standard errors, per profile, Grade 3.

Profile	Relatively low on all variables (blue)		Relatively uninterested very high achievers (orange)		Motivated (yellow)	
	Mean (SE)	Variance (SE)	Mean (SE)	Variance (SE)	Mean (SE)	Variance (SE)
Math achievement	1.15 (0.05)	0.14 (0.02)	1.62 (0.11)	0.45 (0.19)	1.28 (0.08)	0.29 (0.07)
Fluency	0.40 (0.11)	0.77 (0.14)	0.93 (0.16)	0.86 (0.19)	1.00 (0.13)	0.73 (0.16)
Intelligence	0.43 (0.09)	0.52 (0.09)	0.88 (0.13)	0.64 (0.14)	0.55 (0.14)	0.86 (0.17)
Visual-spatial WM	0.33 (0.11)	0.77 (0.15)	0.52 (0.11)	0.46 (0.10)	0.29 (0.13)	0.71 (0.17)
Verbal WM	0.38 (0.10)	0.58 (0.11)	0.76 (0.11)	0.42 (0.10)	0.35 (0.12)	0.58 (0.13)
Interest	0.12 (0.11)	0.70 (0.13)	0.01 (0.15)	0.77 (0.17)	1.07 (0.02)	0.02 (0.00)
Perceived competence	0.26 (0.08)	0.32 (0.06)	0.97 (0.05)	0.07 (0.02)	1.11 (0.04)	0.08 (0.02)
Anxiety	0.01 (0.10)	0.56 (0.10)	−0.73 (0.03)	0.03 (0.01)	−0.89 (0.01)	0.00 (0.00)

Note. Contrary to Fig. 1, the scores for Anxiety have not been reverse-coded.

Table A2.2
Estimated means and variances with standard errors, per profile, Grade 4.

Profile	Relatively unmotivated (green)		Moderately motivated (orange)	
	Mean (SE)	Variance (SE)	Mean (SE)	Variance (SE)
Math achievement	1.20 (0.04)	0.09 (0.02)	1.44 (0.07)	0.29 (0.05)
Fluency	0.63 (0.12)	0.86 (0.15)	0.67 (0.13)	1.01 (0.18)
Intelligence	0.70 (0.09)	0.44 (0.08)	0.64 (0.10)	0.50 (0.10)
Visual-spatial WM	0.54 (0.12)	0.88 (0.15)	0.51 (0.12)	0.75 (0.14)
Verbal WM	0.50 (0.08)	0.31 (0.07)	0.41 (0.11)	0.71 (0.13)
Interest	0.48 (0.11)	0.69 (0.13)	0.03 (0.12)	0.80 (0.14)
Perceived competence	0.96 (0.06)	0.24 (0.04)	0.29 (0.09)	0.43 (0.08)
Anxiety	−0.88 (0.04)	0.06 (0.01)	0.20 (0.10)	0.47 (0.09)

Note. Contrary to Fig. 2, the scores for Anxiety have not been reverse-coded.

Table A2.3
Estimated means and variances with standard errors, per profile, Grade 5.

Profile	Relatively unmotivated with relatively low fluency (purple)		Motivated, especially confident (orange)		Relatively low on all variables (blue)		Motivated (yellow)	
	Mean (SE)	Variance (SE)	Mean (SE)	Variance (SE)	Mean (SE)	Variance (SE)	Mean (SE)	Variance (SE)
Math achievement	1.36 (0.09)	0.28 (0.06)	1.41 (0.10)	0.42 (0.09)	0.92 (0.03)	0.03 (0.01)	1.59 (0.16)	0.74 (0.18)
Fluency	0.43 (0.17)	1.18 (0.25)	1.00 (0.13)	0.70 (0.16)	0.25 (0.19)	0.84 (0.25)	0.84 (0.13)	0.39 (0.11)
Intelligence	0.94 (0.09)	0.36 (0.07)	1.01 (0.08)	0.27 (0.06)	0.10 (0.19)	0.82 (0.21)	0.60 (0.11)	0.34 (0.09)
Visual-spatial WM	0.89 (0.12)	0.48 (0.13)	0.39 (0.13)	0.72 (0.16)	−0.29 (0.19)	0.57 (0.18)	0.53 (0.11)	0.28 (0.08)
Verbal WM	0.65 (0.08)	0.23 (0.05)	0.47 (0.11)	0.49 (0.11)	−0.01 (0.16)	0.53 (0.14)	0.17 (0.21)	1.24 (0.32)
Interest	0.02 (0.13)	0.64 (0.15)	0.64 (0.17)	1.18 (0.26)	−0.24 (0.18)	0.80 (0.22)	0.67 (0.12)	0.37 (0.11)
Perceived competence	0.29 (0.08)	0.24 (0.05)	1.38 (0.06)	0.11 (0.03)	0.16 (0.13)	0.43 (0.12)	1.13 (0.07)	0.11 (0.03)
Anxiety	0.00 (0.10)	0.38 (0.09)	−1.09 (0.01)	0.00 (0.00)	−0.03 (0.16)	0.71 (0.19)	−0.70 (0.03)	0.03 (0.01)

Note. Contrary to Fig. 3, the scores for Anxiety have not been reverse-coded.

Table A2.4
Estimated means and variances with standard errors, per profile, Grade 6.

Profile	Moderately motivated very high achievers (grey)		Relatively low on all variables (blue)		Motivated, especially confident (orange)	
	Mean (SE)	Variance (SE)	Mean (SE)	Variance (SE)	Mean (SE)	Variance (SE)
Math achievement	1.65 (0.10)	0.28 (0.06)	1.02 (0.02)	0.02 (0.00)	1.42 (0.08)	0.15 (0.05)
Fluency	0.94 (0.13)	0.66 (0.16)	0.21 (0.14)	0.66 (0.16)	1.14 (0.14)	0.57 (0.15)
Intelligence	0.92 (0.10)	0.34 (0.08)	0.54 (0.12)	0.51 (0.11)	0.82 (0.12)	0.41 (0.10)
Visual-spatial WM	0.70 (0.13)	0.55 (0.14)	0.19 (0.14)	0.67 (0.16)	0.51 (0.14)	0.57 (0.15)
Verbal WM	0.12 (0.14)	0.70 (0.18)	0.05 (0.16)	0.95 (0.22)	0.34 (0.12)	0.44 (0.11)
Interest	0.46 (0.13)	0.66 (0.15)	0.02 (0.17)	0.96 (0.22)	0.70 (0.18)	0.90 (0.25)
Perceived competence	0.83 (0.09)	0.30 (0.07)	0.48 (0.10)	0.31 (0.07)	1.54 (0.06)	0.08 (0.03)
Anxiety	−0.43 (0.08)	0.22 (0.05)	0.01 (0.14)	0.71 (0.15)	−1.20 (0.01)	0.01 (0.00)

Note. Contrary to Fig. 4, the scores for Anxiety have not been reverse-coded.

Appendix 3. Justification of cluster labels

We created the cluster labels as follows:

- Due to our selection criterion (top 20 % on the standardised achievement test), most profiles scored in the high range for general achievement. Therefore, we only mentioned general achievement if it was very high ($z > 1,5$) and if the error bars did not overlap with other profiles (therefore, very high achievement was not included in the name of the yellow profile in Grade 5).
- Profiles with relatively low scores ($z < 0.5$) on all variables except general achievement were called 'relatively low on all variables'. The general achievement of these profile was moderate to high, although still relatively low compared to the other profiles. To be consistent across grades, we also used this name if a few variables were on the borderline with moderate (in Grade 6).
- For the remaining profiles, the name included a characterisation of motivation which focused either on the general level of all three motivational variables (e.g., 'motivated' for the yellow profile in Grade 3) or on salient single motivational variables (e.g., 'relatively uninterested' for the orange profile in Grade 3).
- Other variables were mentioned in the profile names only if the profile scored relatively low ($z < 0.5$) on this variable and if this relatively low score was also a distinctive feature of this profile compared to other profiles. For example, in Grade 6, the WM variables did not contribute significantly to the differences between the profiles and were therefore not mentioned in the profile names.

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