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Latent Profile Analysis: Comparison of Achievement versus Ability-Derived Subgroups of Mathematical Skills

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Abstract

This study compares latent profiles derived from student subgroups of varying levels of mathematical skills defined by achievement and ability assessment scores. Achievement and ability cut scores for identifying students at both ends of the mathematics spectrum were applied and the resulting latent profiles within each condition were compared. The research utilized latent profile analysis to identify student profiles with achievement scores from the Iowa Assessments and ability scores from CogAT. The participants consisted of 50,998 second-grade students in a Southeastern state. The finding revealed varying demographics and patterns of ability and achievement for each condition, underscoring the need to acknowledge students with diverse learning styles and the distinct dynamics between achievement and ability scores to use for identifying students who may benefit from tailored educational programs.

Keywords:

Mathematical Skills, Ability Assessment, Achievement Assessment, Latent Profile Analysis, CogAT

Introduction

The COVID-19 pandemic significantly disrupted teaching and learning processes, leading to notable declines in student achievement across grade levels. Numerous reports have examined the pandemic's impact, consistently highlighting that mathematics achievement suffered more than reading (Curriculum Associates, 2020; Kuhfeld et al., 2020; Renaissance Learning, 2021). Even prior to the pandemic, academic performance in the United States revealed concerning trends, with 30% of Grade 12 students performing below the basic level in reading and 40% below the basic level in mathematics (National Center for Educational Statistics, 2019). Mathematics, especially, poses challenges for many students and often serves as a gatekeeper to higher education and employment opportunities in technology-driven fields (Moses & Cobb, 2001). The cumulative nature of mathematical learning, where advanced concepts build on foundational skills, further exacerbates difficulties for students who fall behind, making it challenging for them to catch up with their peers (Green et al., 2017).

Given these challenges, understanding how to enhance academic achievement, particularly in mathematics and reading, is a pressing concern for parents, educators, and policymakers (Younger, et al., 2024). Developing targeted strategies to support skill acquisition in these areas is essential, as they form the foundation for broader educational and professional success. Understanding and addressing these issues is important to improve outcomes and ensure equitable opportunities for all students.

In many educational systems, students are traditionally grouped based on cognitive abilities, achievement scores, and other measures to provide more targeted instruction to students with shared strengths or weaknesses. These categories often include students identified as gifted and talented or those participating in individual or intervention education programs. While such groups are more homogenous in terms of selection criteria, studies show that diverse profiles often arise due to various factors reflecting a range of educational, cognitive and social influences (e.g., Mahatmya et al., 2023; Mammadov et al., 2016; Ziernwald e al, 2022) . For instance, some students may excel in specific areas (e.g., math, verbal reasoning) but not necessarily across all domains. "Twice-exceptional" students – those who are both gifted and have learning disabilities – may show discrepancies between achievement and ability scores (Moon & Reis, 2004). Socioeconomic background also plays a role, for example, with high-SES students often benefiting from more exposure to advanced learning resources, resulting in higher achievement scores, while low-SES students may underperform despite having high ability.

Another source of diversity with these groups arises from the tools used to identify students, such as achievement and ability tests along with other measures. Therefore, it is important to distinguish between achievement and ability, as these constructs, while related, assess different aspects of student performance. Achievement typically refers to the knowledge and skills a student has acquired through learning and education, often reflected through test scores and grades (Soares, et al., 2015). In contrast, ability–sometimes referred to as fluid intelligence (Cattell, 1963, 1987)–is typically measured by tests of inductive and deductive reasoning, assessing a student's potential to think critically, solve problems, draw inferences, identify relationships, and transform information in a significant way (Nickerson, 2011). That is, the ability reflects potential, whereas achievement represents the realization or execution of that potential (Schneider, 2013). Understanding the differences between these two constructs is essential for accurately identifying students' needs, as a high-achieving student may not necessarily possess the highest levels of innate ability, and vice versa.

The association between ability and academic achievement is well-established. A large body of research has demonstrated a significant correlation between ability and achievement, ranging from .50 to .70 (Soares, et al., 2015). Variable-centered approaches (e.g., analytic approaches that examine associations among variables; Laursen & Hoff, 2006), such as an ordinary least squares regression, may offer a limited perspective of student performance, potentially obscuring significant subgroups with unique achievement and ability performance patterns because they focus on inter-individual differences instead of intra-individual differences (Litkowski, et al., 2020). In contrast, latent profile analysis (LPA), a person-centered approach, identifies groups of individuals who share certain characteristics (Laursen & Hoff, 2006). By clustering students into latent profiles that reflect shared characteristics across achievement and ability metrics, LPA provides a more nuanced understanding of student diversity and performance.

The existing literature includes studies examining latent profiles of critical thinking and science achievement (Hwang et al., 2023), as well as cognitive profiles based on executive functioning to predict academic performance in reading and mathematics (Carriedo, et al., 2024; Younger, et al., 2024; Litkowski, et al., 2020), and exploration of latent profiles of mathematics achievement, numerosity, and math anxiety in twins (Hart et al., 2016). Additionally, research has explored unique profiles of high-ability and underrepresented students' subject-specific psychological strengths (Mahatmya et al., 2023) and has emphasized the role of LPA in understanding personality profiles of high ability students *L-Ach* (Mammadov et al., 2016). Furthermore, Zierwald et al. (2022) utilized the LPA to differentiate high-achieving subgroups based on different mathematic achievement indicators and the motivational-affective characteristics. Despite these contributions, to our knowledge, thus far, no study has explicitly addressed the heterogeneity in students' performance across both achievement and all components of reasoning ability scores, particularly within the context of high- and low-performing groups.

Therefore, this study aims to explore how high- and low-performing groups, as defined by standardized achievement and ability test scores, differ in their latent profiles derived from standardized achievement (Mathematics and Reading) and ability (Verbal, Quantitative and Nonverbal) tests scores. Specifically, it seeks to answer four major research questions:

1. Do low-achieving and low-ability groups, as defined by achievement and ability test scores, have configural differences (number and shape of profiles) in the latent profiles derived?
2. Do high-achieving and high-ability groups, as defined by achievement and ability test scores,

have configural differences in the latent profiles derived?

3. What are the demographics of students within each of the latent profiles?

4. How do the patterns of test and skill level performances compare across student profiles?

Understanding these profiles has significant implications for educational practitioners. For instance, recognizing that students may differ significantly in terms of learning preferences, strengths, or areas of struggle can inform the design of differentiated instruction, more targeted interventions or support mechanisms tailored to address each subgroup's specific needs. By focusing on both ends of the achievement and ability spectrum, this study offers comprehensive insights into how these student groups differ not just on performance measures but also in their latent academic profiles, potentially guiding future educational policies and practices.

Method

Participants. This study utilized one year of data from one large, diverse school district in the Southeast United States. The data contained 55,482 Grade 2 students who tested with both an achievement and an ability assessment in October of 2022. After excluding individuals who failed to complete the test, encountered testing irregularities, or lacked scores in any of the Iowa Assessments subjects or any of the Cognitive Abilities Test (CogAT) batteries, the remaining 50,998 (49.8% female) test takers were considered in this study.

The demographics in the study samples were as follows: 64% White, 35.3% Black, 12.7% Hispanic, 3.3% Asian, 1% Pacific Islander, and 3.3% students who identified as American Indian or Alaskan Native. Coding was based on information provided by the district for the CogAT. For the race/ethnicity data fields, students were allowed the option to mark all that apply; therefore, the sum of the percentages may exceed 100%. The demographics and summary statistics of the conditions investigated are provided in the data analysis section.

The second-grade data were selected as this grade provides math instruction that involves a diverse range of foundational skills (see Table A1 in the appendix) and most educational systems administer the CogAT for their gifted/talented screening at this grade level. Institutional Review Board (IRB) approval from [blinded] was not required, as the study involved only secondary data analysis using non-identifiable data elements. However, the researchers did not obtain permission from the school district to make the data publicly accessible. Also, neither student nor district-level information is publicized.

Measures. Data from the following measures were collected as a part of the district's planned assessment schedule. De-identified data from these assessments, along with demographic information were provided for this study.

The Iowa Assessments (Dunbar & Welch, 2015). The achievement test was developed with multiple test levels spanning Grades K to 12 that measure knowledge of subject areas that students are expected to have learned at school (e.g., Reading and Mathematics). The content coverage reflects extensive research by an experienced development team using established professional content standards listed in Table A2 (Riverside Insights, 2012). See Table A1 for the skill domains reported for the test level administered for this study. Students' data from Level 7 of the Iowa Assessments Form G Core Battery: Reading (Part 1—Picture Stories and Sentences and Part 2—Stories) and Mathematics (Part 1 and Part 2) were used in this study. These tests vary in length from 35 to 41 questions, and although the tests are untimed, the estimated time for a student to respond to both parts of a test ranges from 45 to 50 minutes. Except for the Reading test, questions are presented orally. To obtain a Reading score and a Mathematics score, both parts of each of the tests must be administered.

The CogAT (Lohman & Lakin, 2017). The cognitive reasoning ability test was developed to span Grades K to 12 for students aged 4 years 11 months to 21 years 7 months and has two alternate test forms designed to be parallel in test structure and item difficulty. The test assesses inductive and deductive reasoning, classified as fluid-analytic abilities (Cattell, 1963; 1987), in three domain areas—nonverbal/figural, verbal, and quantitative reasoning. These abilities are closely related to an individual's success in school and the test results may be used to help plan adaptable instruction. The data used in this study is from the Level 8 tests of Form 8. For this level, tests vary in length from 14 to 18 questions, and although all the tests are untimed, the estimated time for a student to respond to each test ranges from 11 to 15 minutes.

Data Analysis

Two conditions were established to classify students: those scoring in either the lower end (L) or upper end (U) of the score distribution, as determined by norm-referenced scores. The classification was based on the National Percentile Rank (NPR) for either the mathematics test of the Iowa Assessments (mathematics achievement) or the quantitative reasoning battery of the CogAT (quantitative reasoning ability). CogAT provides two types of percentile rank scores: age-based and grade-based. For this study, we utilized the age-based percentile rank. Within each condition, students were identified using achievement (Ach) and ability (Abl) test-based cut scores corresponding to the 23rd and 77th percentile ranks (Jesson, 2018) for the L and U conditions, respectively. For instance, examinees whose national percentile ranks for the Iowa Mathematics test are lower than or equal to 23 composed the lower achievement group (*L-Ach*), and examinees with age-based national percentile ranks higher than or equal to 77 for the CogAT Quantitative Battery composed the upper ability group (*U-Abl*). Figure 1 displays the subgroups created based on these thresholds.

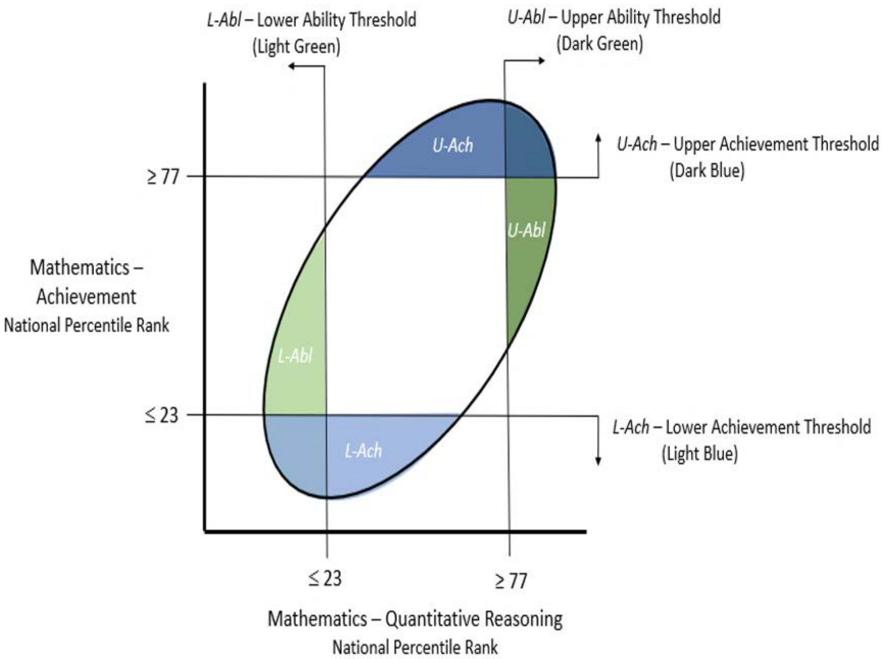
These cut-off scores were selected because they align with the percentile rank thresholds used to define below-average (stanine scores of 1 through 3) and above-average (stanine scores of 7 through 9) performance on both the Iowa and CogAT (Lohman, 2013) assessments. The use of these stanine-based thresholds is particularly relevant because the differentiated instruction reports and profile scores provided by the CogAT assessments are also based on stanine scores (Lohman, 2013). Consequently, these scores are familiar to instructors and have been widely utilized to guide tailored instructional practices.

The demographics of subgroups are provided in Table 1. The achievement-based selection provided the largest sample size in the lower condition while the ability-based criteria selected the largest sample size in the upper condition. Female (52.3%) and black (50.2%) students slightly dominated the *L-Ach* group whereas the *L-Abl* group was slightly dominated by male (52.6%) and black (52.9%) students. Male and white students, on the other hand, dominated both *U-Ach* (60.9%; 87.3%, respectively) and *U-Abl* (56.6%; 80.2%, respectively) groups. In the upper condition, ability-based selection increased the representation of both female and underrepresented groups (Black and Hispanic) compared to the achievement-based selection.

The rescaling of variables before conducting latent profile analysis is a widely common methodological application to ensure interpretable latent profiles (e.g., Carriedo et al., 2024; Spurk et al., 2020). Therefore, the *Iowa Assessments* scale scores (Mathematics and Reading) were rescaled to be on the same scale as the *CogAT* ability normative scale scale ($\bar{x}$ = 100, *SD* = 16). The descriptive statistics of rescaled scores of subgroups *(L-Ach, L-Abl, U-Ach, U-Abl)* are presented in Table 2 to provide an overview of the performance of subgroups on each test. The achievement-based subgroups *(L-Ach & U-Ach)* had higher average test scores than the ability-based subgroups in their specific conditions. In the lower condition, the largest performance differences were on the ability tests whereas the largest performance gaps between the subgroups in the upper condition were on the achievement tests.

To address the research questions, latent profile analyses were conducted using the tidyLPA package (Rosenberg et al, 2019) in R (R Core Team, 2023) for all four subgroups of students (*L-Ach*, *L-Abl*, *U-Ach*, *U-Abl*). Iowa achievement test scores (Iowa Mathematics and Iowa Reading) and *CogAT* ability test scores (Verbal, Quantitative, and Nonverbal Reasoning) were employed to construct student profiles. *LPA* was used as an exploratory-driven approach, and a variety of

Figure 1.
Ability/achievement subgroups based on the thresholds.



models were investigated to determine the optimum number of profiles. This exploratory-driven approach is appropriate where there is no strong theory to suggest or predict the number of classes or profiles that will result from the underlying variables (Hwang et al., 2023). As with other latent variable models, the model fit indices provided in LPA enable different models to be compared and informed decisions to be made regarding the number of underlying classes which is most congruent with the data (Marsh et al., 2009).

An analytic hierarchy process (Akogul & Erisoglu, 2017), based on the Akaike Information Criterion (AIC, Akaike, 1974), Approximate Weight of Evidence (AWE, Banfield & Raftery, 1993), the Bayesian Information Criterion (BIC, Schwarz, 1978), Classification Likelihood Criterion (CLC, Biernacki & Govaert, 1997), and Kullback Information Criterion (KIC, Cavanaugh, 1999), were examined to determine the optimal number of latent profiles for each set of students. For the model fit indices, models with lower values indicate better fit. In addition to relying on model fit indices, the bootstrap likelihood ratio test (BLRT; McLachlan & Peel, 2000) was utilized to assess model adequacy. A statistically significant BLRT result indicates rejection of the null hypothesis of k profiles in favor of a model with k+1 profiles. Other considerations in selecting the optimal model included profile sizes (Lubke & Neale, 2006) and the interpretability of the profiles (Marsh et al., 2009). After identifying the final model, the descriptive statistics and prevalence of each profile were summarized and examined. The latent profiles resulting from the achievement versus ability test-based cut scores were compared for both conditions

Table 1.

Demographic Distributions of the Matched Datasets by Condition and Subgroup.

Condition	Subgroup	*N*	Female	Male	American Indian	Asian	Black	Hispanic	Pacific Islander	White	Other
Lower	*L-Ach (Math NPR ≤ 23)*	22288	52.3%	47.6%	4.5%	2.1%	50.2%	17.4%	1.2%	49.0%	1.1%
	L-Abl (Quant NPR ≤ 23)	8650	47.2%	52.6%	4.1%	1.2%	52.9%	14.8%	1.1%	46.8%	1.3%
Upper	*U-Ach (Math NPR ≥ 77)*	5673	39.1%	60.9%	1.4%	6.7%	10.1%	5.0%	0.5%	87.3%	0.9%
	U-Abl (Quant NPR ≥ 77)	12353	43.4%	56.6%	2.2%	6.6%	16.8%	9.2%	0.7%	80.2%	1.0%

Table 2.

Descriptive Statistics for the Matched Datasets by Condition and Subgroup.

			Achievement								Ability	
			Mathematics		Reading		Verbal		Quantitative		Nonverbal	
Sample	Condition	Subgroup	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Ability/ Achievement Matched Sample	Lower	*L-Ach*	85.3	8.7	90.4	11.9	87.7	11.8	92.5	12.3	88.0	11.4
		L-Abl	83.9	11.5	87.5	11.5	81.2	11.1	79.2	7.6	80.6	9.6
	Upper	*U-Ach*	127.1	6.1	117.8	13.1	113.1	10.5	118.3	10.0	116.7	13.2
		U-Abl	114.8	12.2	111.4	14.7	109.3	10.7	119.3	6.3	113.3	12.6
	Overall	Total Group	100.0	16.0	100.0	16.0	96.9	14.1	102.0	14.3	97.6	15.4

Note: The Iowa Assessments scale scores (Mathematics and Reading) were rescaled to be on the same scale as the CogAT ability normative scale ($\bar{x}$ = 100, *SD* = 16). The total group is comprised of all examinees (*N=50998*) in the matched sample.

Table 3.

Model Fit Statistics for Models for Each Condition and Subgroup.

Condition	Subgroup	Model	LL	AIC	BIC	Entropy	n-min%	BLRT
Lower	*L-Ach*	1	-409398.89	818837.79	818998.03	1.00	100.00%	n/a
		2	-406727.98	813537.95	813866.43	0.70	32.42%	p<.01
		3	-405812.49	811748.98	812245.71	0.61	29.69%	p<.01
		4	-405604.68	811375.37	812040.35	0.54	6.42%	p<.01
		5	**-405430.73**	**811069.46**	**811902.69**	**0.49**	**16.63%**	**p<.01**
		6	n/a	n/a	n/a	n/a	n/a	n/a
	L-Abl	1	-157485.99	315011.98	315153.28	1.00	100.00%	n/a
		2	-155936.00	311953.99	312243.67	0.55	46.80%	p<.01
		3	-155589.40	311302.81	311740.86	0.53	18.55%	p<.01
		4	-155245.08	310656.16	311242.58	0.56	20.18%	p<.01
		5	**-155112.84**	**310433.69**	**311168.48**	**0.53**	**9.78%**	**p<.01**
		6	n/a	n/a	n/a	n/a	n/a	n/a
Upper	*U-Ach*	1	-103674.33	207388.66	207521.53	1.00	100.00%	n/a
		2	-102729.64	205541.28	205813.66	0.50	30.88%	p<.01
		3	**-102276.65**	**204677.29**	**205089.19**	**0.66**	**8.27%**	**p<.01**
		4	n/a	n/a	n/a	n/a	n/a	n/a
		5	n/a	n/a	n/a	n/a	n/a	n/a
		6	n/a	n/a	n/a	n/a	n/a	n/a
	U-Abl	1	-227326.56	454693.13	454841.56	1.00	100.00%	n/a
		2	-225648.74	451379.49	451683.78	0.54	40.33%	p<.01
		3	-224991.37	450106.74	450566.88	0.58	25.58%	p<.01
		4	**-224642.41**	**449450.83**	**450066.82**	**0.65**	**11.31%**	**p<.01**
		5	-224279.65	448767.30	449539.15	0.63	11.06%	p<.01
		6	-224216.03	448682.06	449609.76	0.61	10.53%	p<.01

Note: Bolded is the selected model. LL = Log-likelihood; AIC = Akaike information criteria; BIC = Bayesian information criteria; n-min% = the profile with the smallest percentage of individuals assigned to it; BLRT = The Bootstrap Likelihood Ratio Test; n/a = used to represent nonconvergence or not applicable conditions.

(Lower: *L-Ach* vs. *L-Abl* and Upper: *U-Ach* vs. *U-Abl*). To address the third research question, the percentage distribution of individuals within each profile across demographic categories (e.g., gender and ethnicity) was analyzed. For the final research question, Reading and Mathematics skill scores were summarized across profiles and conditions to compare their patterns to both that of the national averages and within each condition.

Results

A series of LPA models with various constraints (EEI: Equal variances and zero covariances; VVI: Varying variances and zero covariances; EEE: Equal variances and equal covariances; VVV: Varying variances and varying covariances) and up to six profile solutions were run to examine and determine the number of latent profiles for each subgroup. Among all models, solutions with the VVV model provided the best model fit statistics than the others. That is expected since the VVV model is less parsimonious than all the other models yet has the potential to allow for understanding many aspects of the variables that are used to estimate the profiles (Rosenberg et al, 2019). Therefore, fit indices for each solution with only the VVV model are reported in Table 3.

The analytic hierarchy process suggested a five-profile solution for *L-Ach, L-Abl and U-Abl* subgroups but three profiles for the *U-Ach* group. Four, five, and six-profile solutions with the VVV model did not converge for *U-Ach* whereas a six-profile solution did not converge for the *L-Ach*, and *L-Abl*. Even though the fit indices supported a five-profile solution over a four-profile solution for the *U-Abl* subgroup (*BIC* = 449539.15; entropy = 0.63; *BLRT* = 776.60; $p < 0.01$), we determined that the fifth profile had already been represented by another profile with a very slight difference in means at three points (Mathematics, Verbal, and Quantitative). Therefore, the fifth profile did not add meaningful and important information about the heterogeneity in this subgroup. Table 4 provides the mean and standard deviations, as well as the corresponding proportions for each of the latent profiles across the conditions.

Figures 2 & 3; and 4 & 5 visually depict the profiles of the subgroups at the lower and upper conditions, respectively. As is typical in LPA, the naming of profiles is informed by the shape of the profiles. After a thorough examination of Figures 2, 3, and Table 4, we decided that the profile distinction was based on both the general relative performance across the achievement and ability tests and the relative performance between the achievement tests for the *L-Ach* group. These labels are (a) high performance (High), (b) medium performance (Medium), (c) medium performance with Reading strength (Medium-RS), (d) low performance (Low), and (e) low performance with Math weakness (Low-MW). For the *L-Abl* group, the achievement performances were generally higher than the ability performances within profiles (Ach > Abl). Therefore, the distinction was based on the relative performance comparison between the achievement and ability tests for this subgroup. These profile labels are (a) high achievement-high ability

Table 4.

Descriptive Statistics for Achievement and Ability Measures with Sample Sizes Across Latent Profiles and Subgroups.

				Achievement				Ability					
		Sample Size		Reading		Mathematics		Verbal		Quantitative		Nonverbal	
Subgroup	Profile	*N*	*%*	*Mean*	*SD*	*Mean*	*SD*	*Mean*	*SD*	*Mean*	*SD*	*Mean*	*SD*
L_Ach	High	6020	27.0%	96.4	12.4	94.9	1.8	95.0	9.5	99.7	9.3	94.2	10.7
	Medium	4316	19.4%	89.4	8.6	88.6	4.2	88.9	9.5	95.5	9.7	88.0	8.9
	Medium-RS	3968	17.8%	94.8	14.4	84.8	5.1	91.9	9.2	96.0	8.6	90.2	9.8
	Low	4278	19.2%	85.7	9.2	81.7	7.1	81.3	11.9	84.8	13.4	84.1	13.5
	Low-MW	3706	16.6%	84.8	8.8	73.1	5.8	80.4	11.2	85.3	11.4	82.2	7.8
L_Abl	HAHA	1610	18.6%	91.9	12.7	92.2	10.8	85.8	9.4	83.1	2.4	83.2	10.9
	High	2035	23.5%	89.4	11.7	87.4	11.1	86.0	9.5	86.8	1.1	84.6	7.6
	HAMLA	846	9.8%	91.8	14.9	88.2	10.7	82.6	9.9	74.1	6.3	79.6	10.2
	Medium	2445	28.3%	83.9	8.6	79.5	8.6	79.6	11.1	80.4	3.8	81.3	8.9
	Low	1714	19.8%	83.2	6.8	75.4	7.4	73.8	10.3	70.5	7.8	74.3	9.2
U_Ach	High	469	8.3%	124.2	10.9	138.7	6.5	119.3	10.6	124.4	8.8	122.8	12.4
	Medium	2383	42.0%	118.5	12.7	128.2	3.4	113.9	10.2	119.0	9.7	118.1	13.1
	Low	2821	49.7%	115.0	13.2	122.3	1.5	110.3	9.8	115.5	9.8	113.1	12.6
U_Abl	High-RS	1397	11.3%	132.8	4.6	120.5	9.9	114.4	10.0	120.0	4.6	117.2	11.4
	High-QS	3475	28.1%	113.0	13.4	120.0	11.6	112.6	10.9	125.4	6.1	119.3	12.8
	Medium	5225	42.3%	107.3	12.8	111.8	11.3	107.1	9.6	116.8	2.6	110.2	11.2
	Low	2256	18.3%	105.3	13.8	108.5	11.3	104.8	9.8	112.6	0.6	106.3	9.9

Note: The Iowa Assessments scale scores (Mathematics and Reading) were rescaled to be on the same scale as the CogAT ability normative scale ($\bar{x}$ = 100, SD = 16). Medium-RS = Medium Performance with Reading Strength; Low-MW = Low Performance with Math Weakness; HAHA = High Achievement High Ability (Ach>Abl); HAMLA = High Achievement Medium/Low Ability (Ach>Abl); High-QS = High Performance with Quantitative Strength; High-RS = High Performance with Reading Strength.

Figure 2.
Profiles of Low Achievement (L-Ach) Subgroup.

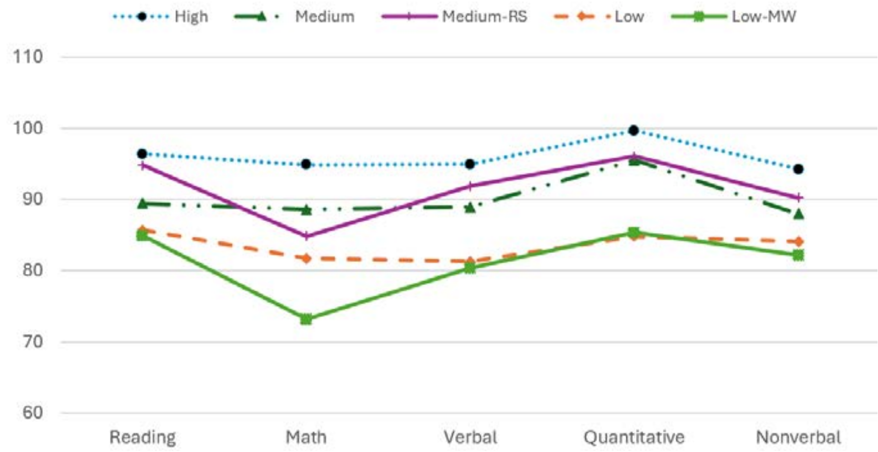
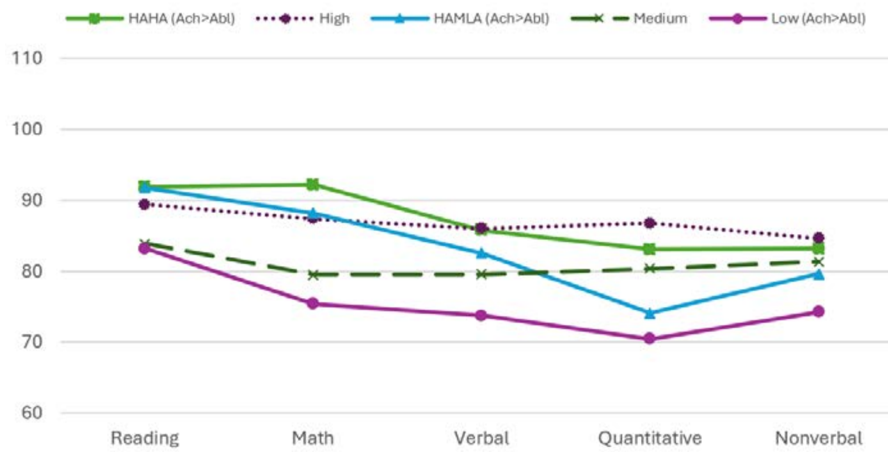


Figure 3.
Profiles of Low Ability (L-Abl) Subgroup.



(HAHA [Ach > Abl]), (b) high achievement-medium/low ability (HAMLA [Ach > Abl]), (c) high performance (High), (d) medium performance (Medium) and (e) low performance (Low [Ach > Abl]).

Naming the profiles of each subgroup for the upper condition was more straightforward than naming the lower condition. After reviewing Figures 4 and 5, the three profiles identified for the *U-Ach* include (a) a high-performance group (High), (b) a medium-performance group (Medium), and (c) a low-performance group (Low) whereas, for the *U-Abl*, the four profiles identified include (a) a high performance with Reading strength group (High-RS), (b) a high performance with Quantitative strength group (High-QS), (c) a medium-performance group (Medium), and (d) a low-performance group (Low).

Subsequently, the detailed findings were discussed in alignment with the research questions outlined in the introduction.

The analysis of low-achieving and low-ability groups to determine potential configural differences (e.g., number and shape of the profiles) revealed that the number of identified profiles remained stable at five, although the patterns within these profiles demonstrated variation. This indicates that the underlying characteristics and interactions between performance metrics differ depending on whether the group is defined by achievement outcomes or inherent ability measures at the lower percentile examinees.

Among the low-achieving group, students displayed relatively lower performance in mathematics compared to their quantitative reasoning abilities, particularly within the Medium-RS and Low-MW profiles. This discrepancy indicates that these profiles may represent students who are underperforming in mathematics relative to their potential in quantitative reasoning. This highlights potential unmet educational needs or contextual barriers affecting mathematics achievement for students in this group. This discrepancy underscores the importance of tailored interventions that bridge the gap between potential and performance.

In the low-ability group, profile patterns were generally consistent across domains; however, notable dips were observed in Quantitative performance for

Figure 4.
Profiles of Upper Achievement (U-Ach) Subgroup.

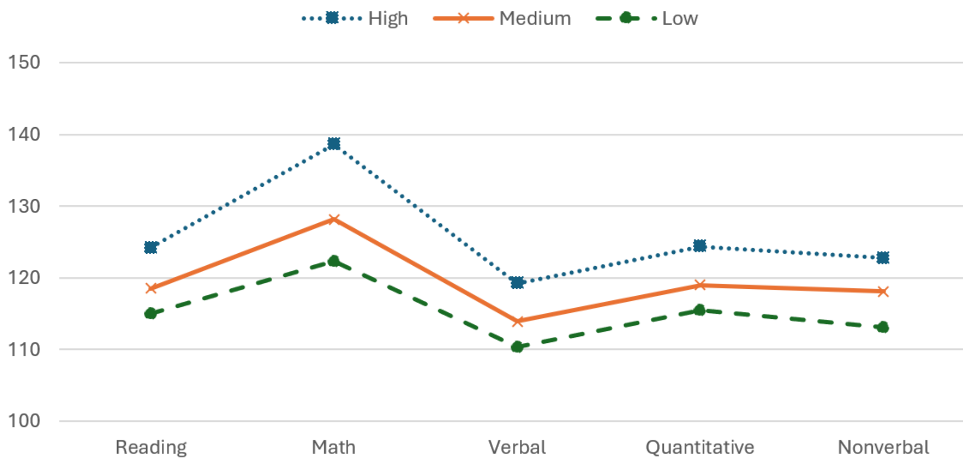


Figure 5.
Profiles of Upper Ability (U-Abl) Subgroup.

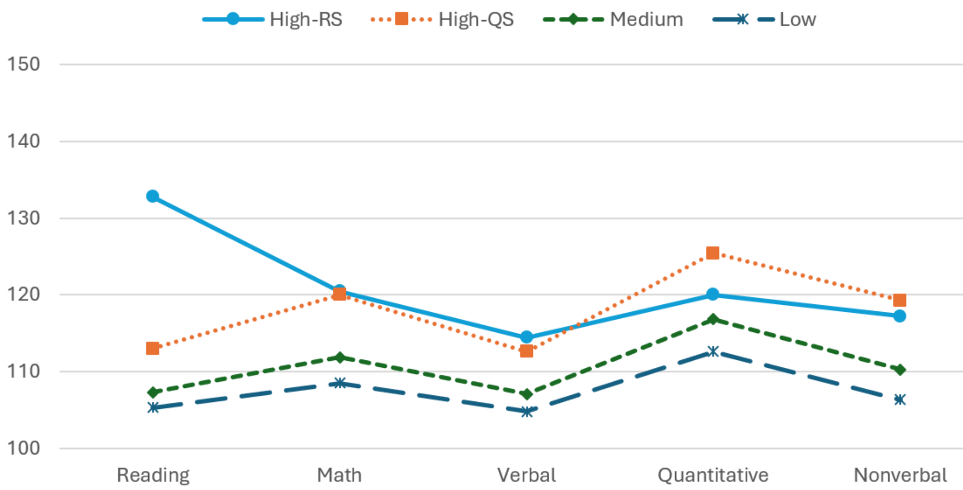


Table 5.
Demographic Distributions for Profiles across Subgroups in Percent.

Subgroup	Profile	*N*	Female	Male	American Indian	Asian	Black	Hispanic	Pacific Islander	White	Other
L_Ach	High	6020	54.5	45.4	3.8	2.9	42.4	14.7	1.0	58.1	1.0
	Medium	4316	50.2	49.7	4.8	2.0	48.5	17.6	1.3	50.0	0.9
	Medium-RS	3968	60.4	39.6	4.2	2.0	52.7	18.4	1.2	47.1	1.0
	Low	4278	47.5	52.3	5.0	1.8	53.2	17.6	1.5	45.1	1.3
	Low-MW	3706	48.2	51.7	5.2	1.6	58.6	20.3	1.2	39.7	1.3
L_Abl	HAHA	1610	50.6	48.9	3.7	0.7	47.1	11.1	0.9	54.8	1.1
	High	2035	50.7	49.1	3.8	1.3	49.9	15.5	0.9	49.3	1.6
	HAMLA	846	47.4	52.4	4.1	0.9	52.1	10.4	0.8	48.8	1.7
	Medium	2445	46.3	53.5	4.3	1.5	56.9	18.2	1.4	42.2	1.1
	Low	1714	41.1	58.7	4.7	1.5	56.5	14.6	1.2	42.1	1.4
U_Ach	High	469	31.6	68.4	1.3	8.3	4.9	4.7	0.2	90.0	1.3
	Medium	2383	36.9	63.0	1.3	7.1	7.9	3.6	0.6	88.7	1.0
	Low	2821	42.1	57.9	1.6	6.1	12.8	6.3	0.5	85.6	0.8
U_Abl	High-RS	1397	58.2	41.7	1.9	6.4	13.1	6.3	0.4	85.1	1.0
	High-QS	3475	32.7	67.2	1.9	9.3	10.6	7.1	0.7	83.0	1.2
	Medium	5225	44.3	55.6	2.6	5.8	19.0	10.8	0.7	78.6	1.0
	Low	2256	48.3	51.6	2.0	4.5	23.4	10.3	0.7	76.2	0.8

Note: Medium-RS = Medium Performance with Reading Strength; Low-MW = Low Performance with Math Weakness; HAHA = High Achievement High Ability (Ach>Abl); HAMLA = High Achievement Medium/Low Ability (Ach>Abl); High-QS = High Performance with Quantitative Strength; High-RS = High Performance with Reading Strength.

the HAMLA and the Low profiles. Students in the HAMLA profile could be considered "over-achievers" in Math given their potential in Quantitative ability. Strategies mitigating the risk of possible burnout may be beneficial for them to continue to excel in Math. The Quantitative and Verbal domains demonstrated the greatest variability across profiles, indicating that these areas were particularly sensitive in distinguishing differences among the latent profiles. Targeted strategies that address variability in quantitative and verbal domains could yield significant improvements.

Building on the distinctions between low-achieving and low-ability groups, a similar analysis was conducted for high-achieving and high ability groups to examine whether the derived profiles exhibit configural differences. The number of derived profile classes and profile patterns for high achieving and high ability groups differed. The profiles in *U-Ach* provided a more general categorization of performance levels (High, Medium, Low), while the *U-Abl* subgroup introduced nuanced distinctions within high-performing profiles, revealing more specific patterns of strength (High-Reading Strength, High-Quantitative Strength). All profiles within the *U-Ach* subgroup demonstrated "over-achievement" in mathematics relative to their potential in quantitative reasoning. Conversely, three profiles within the *U-Abl* subgroup were characterized by "under-achievement" in mathematics whereas the High-RS profile of this subgroup exhibited "over-achievement" in reading. This indicates that the underlying characteristics and interactions between performance metrics differ depending on whether the group is defined by achievement outcomes or inherent ability measures at the upper percentile students as well. The additional granularity in the *U-Abl* subgroup suggests more targeted interventions or instructional strategies based on domain-specific strengths.

Demographic distributions for the latent profiles across subgroups are provided in Table 5. According to the table, for both *L-Ach* and *L-Abl* subgroups, higher-performing profiles (High, Medium) show less demographic diversity than low-performing profiles, which had higher representation from underrepresented groups (Black and Hispanic students). Female representation was higher in high-performing profiles while male representation dominated in most low-performing profiles. Specifically, in the *L-Ach* subgroup, the Medium-RS profile was predominantly composed of female students, whereas the Low-MW profile was primarily comprised of male students. Both profiles, however, were significantly represented by individuals from underrepresented demographic groups, specifically Black and Hispanic students. Gender and demographic differences suggest that these factors may play a role in shaping the latent profiles in the *L-Ach* subgroup and could influence the design of targeted educational support.

For both *U-Ach* and *U-Abl* subgroups, almost all profiles were male and White-dominated. High-RS profile of *U-Abl* was an exception to this as it was dominated by females. Furthermore, higher-performing profiles were less diverse, with higher White representation and fewer underrepresented groups.

Female representation was higher in Reading-specific profiles, such as Medium-RS of *L-Ach* and High-RS of *U-Abl*, while male representation dominates in the Quantitative-specific profiles, like High-QS of *U-Abl*. Regardless of the conditions, low-performing profiles in both achievement and ability-based subgroups consistently had higher proportions of Black and Hispanic students. Gender and demographic differences indicate that these factors are likely to contribute to the formation of latent profiles and may significantly impact the development of tailored educational plans and support strategies.

The analysis also explored how the patterns of test and skill level performances compare across student profiles. In general, high-, medium-, and low-performing profiles were identified for each condition, highlighting variations among "over-achievers" (*U-Ach*, *L-Abl*) and "under-achievers" (*U-Abl*, *L-Ach*) based on mathematics achievement and quantitative reasoning. The latent profiles in the *L-Abl* subgroup showed more variations in terms of test performance than the others.

Specifically, in the low-achieving group, students exhibited notably weaker performance in mathematics relative to their quantitative reasoning skills, with this trend particularly evident in the Medium-RS and Low-MW profiles. On the other hand, students in the HAMLA profile of low ability group can be classified as "over-achievers" in mathematics given their quantitative ability performance. Within the *U-Ach* subgroup, all profiles displayed "over-achievement" in mathematics compared to their quantitative reasoning abilities. On the other hand, three profiles in the *U-Abl* subgroup showed "under-achievement" in mathematics, while the High-RS profile stood out with "over-achievement" in reading.

Figures 6 and 7 display Mathematics skill scores (percent correct scores), as well as national averages of skill scores, across the profiles of *L-Ach* and *L-Abl* subgroups, respectively. Students across the profiles of both *L-Ach* and *L-Abl* showed similar weaknesses and strengths patterns of Mathematics skills with the national sample but in varying degrees. For instance, Algebraic Patterns and Geometry were consistently strong areas whereas Measurement and Data Analysis areas showed the steepest decline across profiles in both groups. It is noteworthy that as the profiles shift from higher to lower performance levels, geometry skills increasingly dominate over algebraic pattern skills. In contrast, within the higher-performing profiles, algebraic patterns skills are either comparable to or exceed those of geometry, highlighting a distinct shift in skill emphasis across performance tiers. Scores on the Extended Reasoning skill, on the other hand, were generally low, indicating this is a challenging area for all groups.

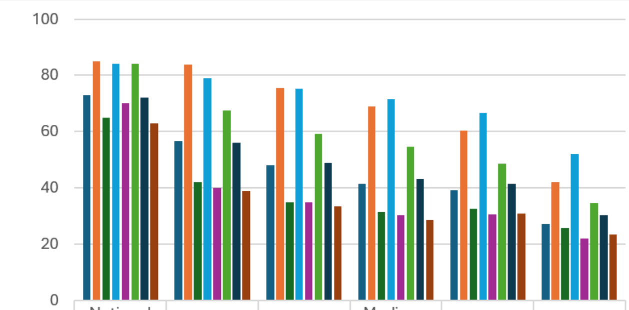
Figures 8 and 9 illustrate a comparison of skill scores across profiles of *U-Ach* and *U-Abl* relative to the national average in various mathematical domains. Consistent patterns of strengths and weaknesses were observed across profiles in both groups. Notably, all profiles within the *U-Ach* group outperformed the national averages, whereas Measurement and Extended Reasoning and to some extent the Data Analysis/Prob/Stats skill emerged as persistent challenges in the Medium and Low profiles of the *U-Abl* group. This observation highlights that high quantitative reasoning ability does not necessarily translate into high performance across all areas of mathematical achievement. Targeted efforts to address these areas of difficulty could contribute to reducing performance disparities among students. Patterns of Reading skill scores observed across profiles and conditions were more consistent; therefore, the related plots are provided in the appendix (See Figures A1-A4).

Discussion

The findings highlight substantial differences in the number and patterns of latent profiles across low-achieving (*L-Ach*), low-ability (*L-Abl*), high-achieving (*U-Ach*), and high-ability (*U-Abl*) groups, emphasizing the distinct dynamics between achievement and ability, and reinforcing the notion that achievement and ability represent distinct but related constructs. Moreover, regardless of performance levels, the variations in the latent profiles between ability- and achievement-based groups support previous findings that different tests (Carman et al., 2019) and selection criteria (e.g., Lohman & Renzulli, 2007; McBee et al., 2014; Lakin, 2018) used to categorize students based on performance yield groups with distinct instructional

Figure 6.

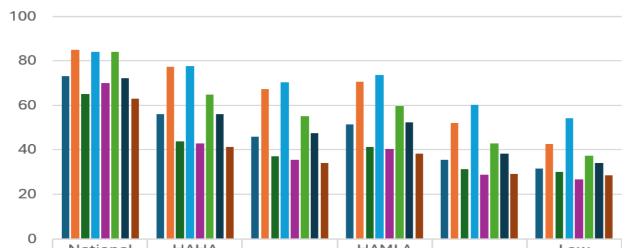
Math Skill Scores of L-Ach Subgroup with National Averages.



	National Avg.	High	Medium	Medium-RS	Low	Low-MW
Number Sense/Operations	73	56,6	48,0	41,5	39,0	27,1
Algebraic Patterns/Connections	85	83,8	75,6	68,9	60,2	41,9
Data Analysis/Prob./Stats	65	41,9	34,8	31,4	32,7	25,6
Geometry	84	79,0	75,2	71,6	66,5	52,1
Measurement	70	40,1	34,8	30,3	30,6	22,0
Essential Competencies	84	67,5	59,1	54,6	48,5	34,6
Conceptual Understanding	72	55,9	48,9	43,1	41,5	30,2
Extended Reasoning	63	38,9	33,4	28,5	30,7	23,4

Figure 7.

Math Skill Scores for L-Abl Subgroups with National Averages.



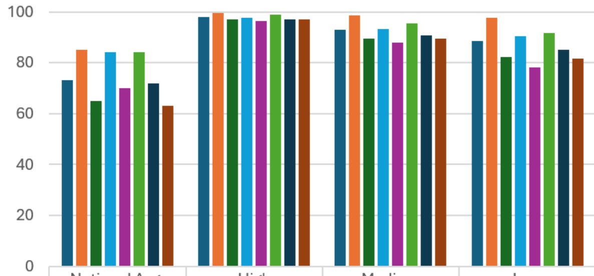
	National Avg.	HAHA (Ach>Abl)	High	HAMLA (Ach>Abl)	Medium	Low (Ach>Abl)
Number Sense/Operations	73	56,1	45,9	51,4	35,5	31,7
Algebraic Patterns/Connections	85	77,3	67,1	70,6	51,9	42,4
Data Analysis/Prob./Stats	65	43,9	36,9	41,5	31,1	30,1
Geometry	84	77,7	70,3	73,8	60,3	54,2
Measurement	70	42,9	35,5	40,4	28,9	26,7
Essential Competencies	84	64,9	55,1	59,8	42,8	37,4
Conceptual Understanding	72	55,9	47,3	52,2	38,2	34,1
Extended Reasoning	63	41,3	34,1	38,4	29,2	28,4

needs, especially in the gifted/talented identification. How you identify determines who you identify (Long et al., 2024).

In general, profiles in the both *L-Abl* and *U-Ach* groups had students exhibited "over-achievement" in mathematics despite lower quantitative reasoning ability is aligned with previous findings on "overachievers", who compensate for lower cognitive ability with higher perseverance, motivation, or access to enriched learning environments (Hofer & Stern, 2016; Ziernwald et al., 2022). Additionally, both the *L-Ach* and *U-Abl* groups had profiles, where mathematics performance lagged behind quantitative reasoning potential, highlighting the possible influence of external factors, instructional quality, and socioemotional barriers on student performance. Ziernwald et al. (2022) similarly reported that fluid intelligence alone does not always predict high academic performance, as motivational-affective factors and educational support structures play a crucial role in the realization of academic potential. Overall, depending on the performance level (Lower vs. Upper) of classification, achievement-based classification often overlooks cognitive potential or vice versa. This finding supports the strong recommendation of the National Association for Gifted Children (NAGC, 2010) for the use of multiple measures, especially when high stakes, test-based decisions are being made such as classroom assignment.

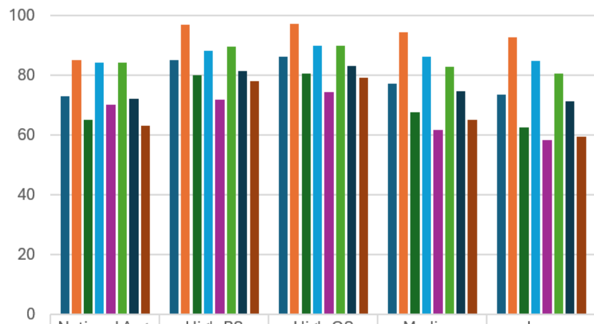
The presence of greater nuance in *U-Abl* profiles, where students displayed domain-specific strengths such as High-Reading Strength (*High-RS*) and High-Quantitative Strength (*High-QS*), as well as the diverse profiles emerged in the other groups, displayed heterogeneity in those clusters and thus the needs of differentiated instructions for the emerged profiles. This is in line with the findings that low- and high-ability students showed a larger intraindividual heterogeneity in ability indicators compared to average-ability students (Lohman et al., 2008)

Figure 8.
Math Skill Scores for U-Ach Subgroup with National Averages.



	National Avg.	High	Medium	Low
Number Sense/Operations	73	97,9	93,0	88,7
Algebraic Patterns/Connections	85	99,6	98,7	97,6
Data Analysis/Prob./Stats	65	97,1	89,6	82,1
Geometry	84	97,7	93,3	90,3
Measurement	70	96,5	87,8	78,1
Essential Competencies	84	99,0	95,4	91,6
Conceptual Understanding	72	96,9	90,8	85,1
Extended Reasoning	63	97,1	89,5	81,8

Figure 9.
Math Skill Scores for U-Abl Subgroup with National Averages.



	National Avg.	High-RS	High-QS	Medium	Low
Number Sense/Operations	73	85,0	86,1	77,2	73,5
Algebraic Patterns/Connections	85	96,8	97,0	94,4	92,4
Data Analysis/Prob./Stats	65	79,9	80,5	67,5	62,4
Geometry	84	88,2	89,6	86,2	84,8
Measurement	70	71,7	74,2	61,6	58,3
Essential Competencies	84	89,4	89,7	82,8	80,4
Conceptual Understanding	72	81,4	83,1	74,5	71,2
Extended Reasoning	63	77,8	79,0	65,0	59,5

Gender distribution analysis of the profiles of each group showed that female representation was higher in Reading-specific profiles, such as *Medium-RS* of *L-Ach* and *High-RS* of *U-Abl*, while male representation dominates in the Quantitative-specific profiles, like *High-QS* of *U-Abl*. This is in accordance with the long history of gender achievement gap in reading (favoring females) and math (favoring males) in the US (e.g., Robinson et al., 2011).

Demographic patterns further underscored systemic inequities, with underrepresented groups (e.g., Black and Hispanic students) predominantly occupying lower-performing profiles across all subgroups, while higher-performing profiles were less diverse and primarily composed of White students. This is consistent with the finding that the type of assessment used to categorize students had only a minor effect on equity (Hodges et al., 2018; Long et al., 2024). These findings suggest the need for interventions that are both domain-specific and equity-focused, targeting disparities in mathematics achievement and quantitative reasoning while also addressing demographic disparities to ensure more inclusive academic success.

Conclusions

This study compared latent profiles derived from student subgroups of varying levels of mathematical skills defined by achievement and ability assessment scores. Achievement and ability cut scores for identifying students at both ends of the mathematics spectrum were applied and the resulting latent profiles within each condition were compared. The best-fitting solution across conditions ranged from 3 to 5 mutually exclusive profile classes that adequately described the variation in the ability and achievement test scores. Varying demographics and patterns of ability and achievement for each condition demonstrate the importance of recognizing students with varying learning styles and the importance of understanding distinct dynamics between achievement and ability scores while using them to identify students who may benefit from targeted instruction or placement in gifted and talented programs.

As schools continue to recover from the impact due to the disruption of the pandemic, efforts to adapt instructional strategies are crucial for ensuring students return to the pre-pandemic learning trajectory. By determining the profile characteristics, findings from this study provide valuable feedback to educators to address areas of greatest need for differentiated instruction and leveraging information regarding student academic profiles.

The LPA method used in this study enhances findings from variable-centered approaches; however, it is important to acknowledge several limitations. First, LPA does not identify "true" subgroups of individuals. Like latent variables, which are inferred from observed variables, the subgroups themselves are unobserved constructs. To address this limitation, we carefully evaluate model fit indices and examine the probabilities of each observation belonging to a given latent profile. Even though the emerged profiles across conditions allowed us to make interpretations like "over" or "under" achievement based on the ability and achievement comparison, LPA was fundamentally used as an exploratory analytical technique. This necessitates caution in drawing definitive interpretations or implications from the findings.

Despite these limitations, this study represents an important exploratory step in identifying potential unique profiles of second graders' achievement and ability performances. The current study is based on one large educational system; therefore, the generalization of the results might be limited. Future research should explore whether these profiles replicate across different populations and settings to validate and extend the current findings. Students interpret their experiences through a combination of cognitive, social, and emotional processes, all of which impact learning (Darling-Hammond & Cook-Harvey, 2018). Given that, one should investigate the connections among them in terms of identifying potential unique profiles. Furthermore, a multiple-group latent profile analysis (Morin, et al., 2016) should be conducted to make direct comparisons within conditions used in this study to investigate the invariance of emerged profiles.

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Appendix A

Table A1.

Skill Definition Table for the Iowa Assessments.

Subject	Skill Domain Description
Reading	Conceptual Understanding Essential Competencies Extended Reasoning Literary Explicit Meaning Implicit Meaning Informational Key Ideas
Mathematics	Algebraic Patterns & Connections Conceptual Understanding Essential Competencies Extended Reasoning Geometry Measurement Number Sense & Operations Data Analysis, Probability, & Statistics

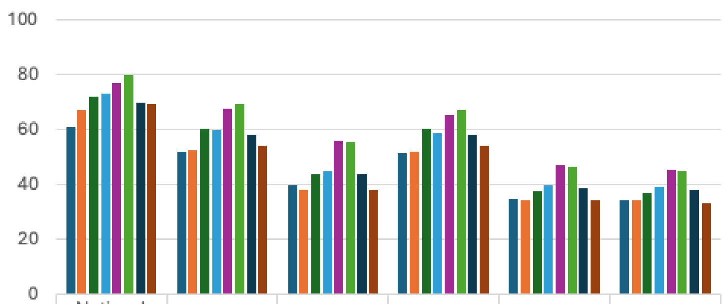
Table A2.

Alignment by Subject of Tests and Standards for the Iowa Assessments.

Subject	Alignment with Standards
Reading	National Council of Teachers of English (NCTE) and International Reading Association (IRA) Standards for the English Language Arts
Mathematics	National Council of Teachers of Mathematics (NCTM) Assessment Standards for School Mathematics; Curriculum and Evaluation Standards for Mathematics

Figure A1.

Reading Skill Scores of L-Ach Subgroup with National Averages.



	National Avg.	High	Medium	Medium-RS	Low	Low-MW
Informational	61	51,8	39,8	51,5	35,0	34,4
Literary	67	52,3	38,2	52,2	34,1	34,0
Explicit Meaning	72	60,1	43,5	60,2	37,6	37,2
Implicit Meaning	73	59,8	45,0	58,9	39,8	39,1
Key Ideas	77	67,4	56,1	65,1	47,3	45,2
Essential Competencies	80	69,1	55,4	66,8	46,7	44,7
Conceptual Understanding	70	58,2	43,9	58,0	38,6	38,4
Extended Reasoning	69	54,3	38,2	54,5	34,5	33,4

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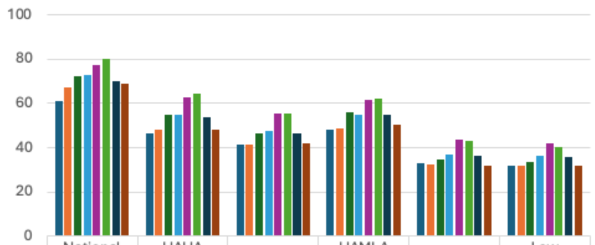
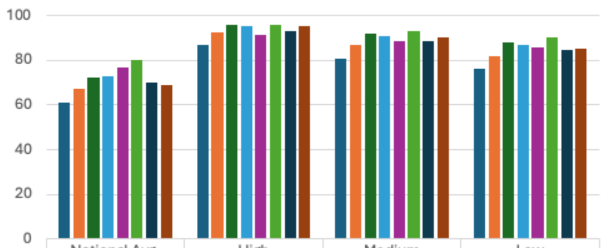
Figure A2.
Reading Skill Scores for L-Abl Subgroups with National Averages.



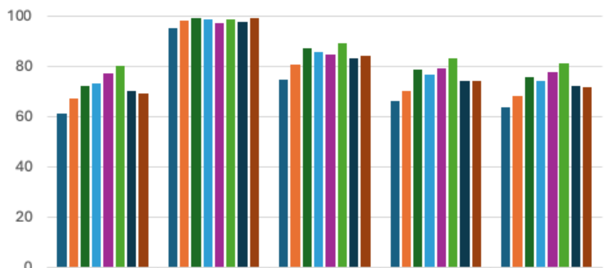
	National Avg.	HAHA (Ach>Abl)	High	HAMLA (Ach>Abl)	Medium	Low (Ach>Abl)
Informational	61	46,4	41,4	48,1	32,8	31,5
Literary	67	48,0	41,4	48,7	32,5	31,9
Explicit Meaning	72	54,8	46,4	55,7	34,9	33,5
Implicit Meaning	73	55,0	47,6	55,1	37,1	36,4
Key Ideas	77	62,8	55,2	61,7	43,8	41,6
Essential Competencies	80	64,3	55,5	62,3	42,9	40,1
Conceptual Understanding	70	53,4	46,3	54,6	36,2	35,7
Extended Reasoning	69	48,1	41,8	50,2	31,9	31,9

Figure A3.
Reading Skill Scores for U-Ach Subgroup with National Averages.



	National Avg.	High	Medium	Low
Informational	61	86,8	80,6	76,4
Literary	67	92,6	86,8	81,9
Explicit Meaning	72	95,9	91,8	88,1
Implicit Meaning	73	95,5	90,8	86,9
Key Ideas	77	91,5	88,3	85,6
Essential Competencies	80	95,9	92,8	90,2
Conceptual Understanding	70	92,8	88,2	84,3
Extended Reasoning	69	95,3	90,0	85,2

Figure A4.
Reading Skill Scores for U-Abl Subgroup with National Averages.



	National Avg.	High-RS	High-QS	Medium	Low
Informational	61	95,1	74,9	66,2	63,9
Literary	67	98,0	80,5	70,1	68,1
Explicit Meaning	72	99,0	87,1	78,5	75,8
Implicit Meaning	73	98,9	85,9	76,7	74,3
Key Ideas	77	97,0	84,6	79,0	77,8
Essential Competencies	80	98,9	89,1	83,2	81,1
Conceptual Understanding	70	97,6	83,4	74,3	72,2
Extended Reasoning	69	99,3	84,1	74,3	71,8