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Research Article

The cognitive profiles of gifted children: A latent profile analysis using the ASIS

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Intelligence scales are widely employed in the assessment of gifted students. The Anadolu-Sak Intelligence Scale [ASIS], an intelligence evaluation tool originating from Turkey, is extensively used for identifying gifted students. This study aimed to investigate the cognitive profiles of gifted children using the ASIS. Participants were selected from students who underwent intelligence testing at the Gifted Education Research and Practice Center [GERPC]. The study focused on data from 360 students with a GIQ score of 130 or higher. To determine the cognitive profiles of gifted students, a statistical technique called latent profile analysis [LPA] was employed using the tidyLPA package in R. The results revealed two distinct gifted profiles: verbal gifted (38%) and nonverbal gifted (62%). Children with a verbal gifted profile excelled in tasks involving verbal reasoning, analogies, and linguistic abilities. Conversely, children with a non-verbal gifted profile demonstrated exceptional abilities in tasks requiring visual flexibility and sequential processing. Both groups exhibited superior cognitive abilities across various domains compared to the average group mean. These findings challenge the notion of a single, general intelligence profile and underscore the importance of considering multiple domains and psychometric categories when identifying and supporting gifted individuals.

Keywords: Giftedness; Cognitive profiles; Latent profile analysis

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1. Introduction

Numerous academic and practical studies have been carried out to define giftedness and identify individuals who possess exceptional abilities. Consequently, the academia engages in several debates regarding the concept of giftedness (Yassin et al., 2012). One of these debates focuses on the individual aspect, which is an essential component of the concept. The core issue under discussion pertains to determining an individual's intelligence through the use of tests. Some experts argue that assigning giftedness to a single numerical value, such as IQ, contradicts scientific principles (Goodhew, 2009). Conversely, another group supports an approach based on IQ scores (Davis, 2011). Nonetheless, proponents of the IQ-based approach assert that several factors need to be considered to effectively identify gifted individuals. These factors include criteria related to individual expression, continuous assessment, and multiple indicators (Brown et

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al., 2005). Furthermore, it is emphasized that intelligence tests must adhere to specific standards (Callahan et al., 1995; Han & Marvin, 2000). These include a) clear definition of giftedness, b) avoid using a single cut-off score, c) consider the multiple manifestations of giftedness, d) use separate tools/instruments to assess the different areas of intelligence, e) be aware that giftedness may come in different forms, f) base identification on students' educational needs and not on program quotas, numbers or slots, and g) repeat assessment over time to identify additional gifted students.

Despite the standardized nature and structured administration procedures of intelligence tests, the scores derived from IQ tests or the designated cut-off scores, which serve as the foundation for intelligence classifications, may occasionally fail to accurately reflect individuals' true capabilities (Gilman et al., 2013; Kaufman, 2009; Silverman, 2018; Wasserman, 2013). While general intelligence scores obtained from these tests are useful for classifying individuals with mental disabilities, they are inadequate for providing comprehensive information about gifted individuals, especially who exhibit complex clinical profiles or form a mentally diverse population. Consequently, alternative approaches have emerged that focus on analyzing performance discrepancies and score patterns on subtests (such as verbal, visual, memory, etc.) or various index scores derived from these subtests (Flanagan & Kaufman, 2009). These approaches aim to provide a more nuanced understanding of gifted individuals' abilities.

The concept of giftedness is complex and influenced by a combination of genetic, personal, and behavioral factors, resulting in a diverse range of profiles among gifted individuals. Various studies have explored these profiles and identified different types of gifted students. For example, Betts and Neihart (1988) developed six profiles, including successful, underground, dropouts, double-labelled, and autonomous learners. In another study, Cho et al. (2008) identified four types based on characteristics such as self-concept, self-efficacy, beliefs about intellectual abilities, motivation for achievement, and attitude toward school. These types were the full-bloomer, good-achiever, fade-away, and late-bloomer. Similarly, Castejon et al. 2016) investigated cognitive and motivational differences among 358 gifted individuals and identified four profiles: gifted achievers, cognitive gifted, creative gifted, and high achievement and cognitive gifted. Additionally, Dixon et al. (2001) identified six groups among 156 gifted students, including a mathematics focus, a social focus, a nonathletic group, a low overall self-concept group, a verbal group, and a nonspiritual/religious group.

It is seen that the mental profiles of gifted individuals, who show a heterogeneous structure, obtained from intelligence tests differ in some studies. For example, in a study using traditional psychometric methods, Benbow et al. (1983) examined the intelligence structure of students with exceptional general abilities. The results showed that academic giftedness consists of at least two different forms. These are verbal and non-verbal giftedness. In a study conducted by Benbow and Minor (1990) with 13-year-old students, the Scholastic Aptitude Test [SAT] was administered to 106 mathematically gifted, 20 verbally gifted, and 18 students who met both verbal and mathematical criteria. As a result of the study, factor analysis was performed with the scores of gifted students from general aptitude tests and according to the intelligence model obtained, it was found that the students had 3 different intelligence profiles. They were labeled spatial/speed, verbal, and nonverbal reasoning.

When experts evaluate the WISC-R profiles of highly intelligent children, they often depend on standard statistical tables and methods. Some of these methods may not be suitable or can be misleading for gifted children, even though they work well for children with average IQ. These conjectures could be intriguing when considering individual evaluations and diagnoses of gifted students. This is because, based on existing literature on giftedness, we already believe that these children exhibit larger discrepancies between Verbal IQ and Performance IQ than children of average intelligence (Silver & Clampit,1990; Sweetland et al., 2006; Wilkinson, 1993). For instance, Silver and Clampit (1990) in their research utilized statistical data from the standardization sample of the WISC-R (2200 children aged 6-16) sourced from the WISC-R manual and various articles that statistically examined the scores of children in the standardization sample to recreate the

"Frequency of Verbal-Performance Discrepancy" tables. They demonstrated in this table that there was a gap of between 9 and 40 points in verbal and performance scores for individuals with an IQ above 124. They argued for a more precise analysis of WISC-R profiles, particularly for gifted individuals. Their research concluded that there are two distinct profiles for verbal and non-verbal abilities.

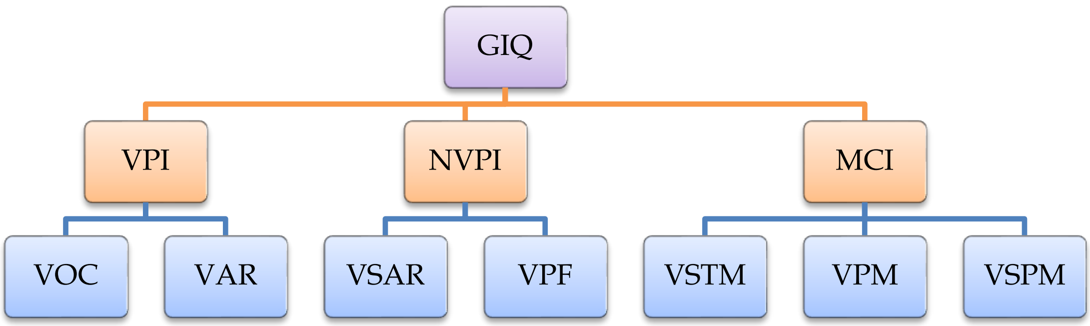
In light of research on the cognitive characteristics of gifted individuals, it is problematic that educational programs for this diverse population rely solely on general intelligence scores for identification. Requiring a minimum IQ score of 130 as the sole criterion for admission to these programs overlooks the specific educational needs of gifted students. This is because the IQ score alone does not provide a comprehensive understanding of a student's strengths, as it can be influenced by various cognitive profiles (Winner, 1996). Therefore, it is crucial to employ domain-specific identification methods or consider different cognitive profile scores alongside general intelligence scores to accurately identify gifted students in specific areas such as mathematics, verbal, etc. By doing so, we can obtain a more comprehensive understanding of a student's abilities and address their educational needs effectively. This study's findings contribute to the ongoing discussion in academic literature about the drawbacks of relying solely on a single intelligence score for diagnostic systems. It highlights the significance of taking into account various cognitive profiles. Thus, the aim of the study is to reveal the cognitive profiles of gifted students by analyzing their intelligence scores derived from the Anadolu-Sak Intelligence Scale (ASIS).

1.1. Anadolu Sak Intelligence Scale

The ASIS is an individually administered intelligence test battery designed for children aged 4-12 years, consisting of seven subtests. The development of the ASIS was based on the Cattell-Horn-Carroll [CHC] model of intelligence (McGrew, 2009; Schneider & McGrew, 2012), incorporating Luria's processing-based neuropsychological model (Das et al., 1979; Luria, 1970) and Baddeley's memory model (Baddeley, 2012) in the creation of the subtests. These subtests are combined to generate three component scores: The Verbal Potential Index [VPI], the Nonverbal Potential Index [NVPI], and the Memory Capacity Index [MCI] (Figure 1). The VPI includes vocabulary [VOC] and verbal analogies [VAR], while the NVPI comprises visual-spatial analogical reasoning [VSAR] and visual perceptual flexibility [VPF]. The MCI encompasses verbal short-term memory [VSTM], visual pattern memory [VPM], and visual sequential processing memory [VSPM]. The General Intelligence Index [GIQ], which encompasses all seven subtests, serves as a measure of general intelligence.

The GIQ serves as a measure of general mental capacity and is considered a component of all mental skills within the theoretical structure of the ASIS. In the CHC model, the VPI is categorized as crystallized intelligence, encompassing skills acquired throughout life, such as verbal comprehension, general knowledge, language development, vocabulary, semantic knowledge, and discipline-specific knowledge (Schneider & McGrew, 2012). The NVPI corresponds to the fluent intelligence component and the visuospatial perceptual processing component, including spatial relations, visual flexibility, visualization, and mental rotation, in the second layer of the CHC model (Schneider & McGrew, 2012). The MCI includes working memory and short-term memory. Working memory involves the limited capacity to store and process information simultaneously, while short-term memory solely focuses on storing information for a brief period (Baddeley, 2012; Dehn, 2014). Working memory is a component in the second layer of the CHC model of intelligence (Schneider & McGrew, 2012). The theoretical structure of the working memory component of ASIS is based on Baddeley's memory model and Luria's neuropsychological processing theory (Baddeley, 2012; Das et al., 1979; Luria, 1970). Both verbal short-term memory (phonological short-term memory) and visual short-term memory are included as sub-factors of working memory in the theoretical structure of ASIS, aligning with Baddeley's memory model. The processing types of the subtests, including sequential and simultaneous processing, as well as attention, are based on Luria's model. Sequential processing refers to the ability to process information in a step-by-step manner, while simultaneous processing involves the ability to process multiple pieces of information simultaneously. Attention refers to the ability to focus and sustain attention on relevant stimuli. By incorporating these theoretical frameworks into the design of the ASIS, the test aims to comprehensively assess various cognitive abilities, providing a more comprehensive understanding of an individual's cognitive profile and mental skills.

Figure 1
The three-factor model of ASIS



1.1.1. The Subtest of ASIS

Vocabolary [VOC]. This subtest measures vocabulary knowledge, which includes understanding the meaning of words, their usage in different contexts, and the ability to identify synonyms and near synonyms. Additionally, it encompasses both conceptual knowledge, such as understanding the ontological aspects of words, and practical knowledge, such as familiarity with common usage. Language development, considered a sub-factor of crystallized intelligence in the CHC model, is an ability that is acquired and developed throughout one's life. It is directly related to word acquisition and the ability to comprehend verbal stimuli.

Verbal analogies [VAR]. This subtest evaluates abstract reasoning and problem-solving abilities, which are widely acknowledged as crucial components of intelligence (Mayer, 1992). It specifically focuses on classical verbal analogy problems. The majority of the analogies in this subtest revolve around semantic relations. They follow a structure similar to "If A:B, then C: ?". For instance, a problem could be presented as follows: "If apples are to fruit, then happiness is to what?" This example illustrates an abstract analogy that pertains to advanced classification.

Visual-spatial analogical reasoning [VSAR]. The purpose of this subtest is to assess abstract thinking and reasoning skills, which are considered high-level abilities, using visual analogies. Visual analogies involve making inferences based on abstract relationships (Sternberg et al., 2008). Since all the items in this subtest consist of abstract shapes, the influence of crystallized intelligence is minimal or negligible. The development of the visual analogy problems drew upon the taxonomy of whole-part relations (Winston et al., 1987) and the structure-mapping theoretical model (Gentner, 1983). These analogies feature abstract shapes presented in 2 x 2 and 2 x 3 matrices, and they exhibit various abstract relationships, such as similarity, contrast, phase-process, class membership, group membership, whole-part, component-part, and ratio.

Visual perceptual flexibility [VPF]. The subtest measures various visual perceptual processing skills, including perceptual discrimination, visualization, visual flexibility, mental flexibility, spatial relations, and visual manipulation. Visual perceptual discrimination ability is categorized within the comprehensive ability group in the second layer of the CHC model and is considered a visual processing component. The development of the VPF subtest drew upon the rotated shape perception model (Takano, 1989), mental rotation of two-dimensional shapes (Cooper, 1975), and mental scaling (Bennett & Warren, 2002). The subtest consists of two types of problems: the first involves the rotation of shapes, while the second incorporates both rotation and scaling.

Verbal short-term memory [VSTM]. This particular subtest assesses verbal short-term memory and is connected to both phonological short-term memory in Baddeley's memory model (Baddeley, 2012) and the attention component in Luria's model (Luria, 1970). It involves a story containing 114 words and 20 questions based on the story. The story is read first, followed by the questions. The answers to the questions can be found within the story's details.

Visual pattern memory [VPM]. This subtest evaluates the concurrent visuospatial processing in Luria's model (Luria, 1970) and the working memory for visuospatial information in Baddeley's memory model (Baddeley, 2012). It involves displaying abstract shapes, specifically triangles, positioned on a grid in various arrangements such as 1x1, 1x2, 2x2, 2x3, 2x3, 3x3, 3x4, 3x4, 4x4, 4x5, 4x5, 5x5, and 6x6. These shapes are shown for 5 seconds, and then the task is to identify the same shape among different shapes.

Visual sequential processing memory [VSPM]. The final subtest assesses visual post-processing in Luria's model (Luria, 1970) and visual short-term memory or visual memory breadth in Baddeley's memory model (Baddeley, 2012). It involves presenting a series of shapes, primarily geometric, on a plane. After the sequence is displayed for 5 seconds, the task is to identify the same sequence among other sequences of shapes.

2. Method

2.1. Participants

The participants of the study selected among students who were administered intelligence tests at the Gifted Education Research and Practice Center [GERPC]. ÜYEP was established in 2007 as an education program for gifted students with the support of the Scientific and Technological Research Council of Türkiye, and was transformed into an application and research center in 2014. The center provides scientific research and education services for gifted students, as well as the identification of children by conducting intelligence tests with a team of experts. Children get at least 130 IQs accepted as gifted according to ASIS. So the study included 386 gifted students who achieved a minimum of 130 GIQ points out of a total of 4063 children who underwent ASIS testing at the GERPC between 2016 and 2021. Table 1 provides details on the participants' attended class and gender variables. The age range of the participants was between 4 and 12 years old.

Table 1
The demographics of the recruited study participants

Class	*Boy*	*Girl*	*Total*
Preschool	98	47	145
1	14	16	30
2	4	6	10
3	10	3	13
4	12	9	21
5	61	53	114
6	30	23	53
Total	229	157	386

2.2. Data Collection Tool

2.2.1. Anadolu Sak Intelligence Scale (ASIS)

In the research, ASIS served as the primary instrument for gathering data. It was described in detail above. It is an individually administered intelligence test consisting of 256 items, seven subtests, and three factors. Developed as the initial measure for evaluating the intellect of Turkish-speaking children between the ages of 4 and 12 (Sak et al., 2016), ASIS is particularly employed for identifying and analyzing the profiles of children exhibiting giftedness, intellectual developmental challenges, learning difficulties, and attention deficits. Beyond its clinical and educational uses, ASIS is also applicable to various scientific investigations, such as forecasting academic achievement, cognitive abilities, and uncovering the connections among exceptional talents, intelligence, and creativity.

Numerous research studies have examined the reliability and validity of the ASIS (Arslan & Sak, 2023; Cirik et al., 2020; Sak et al., 2016; Sözel et al., 2018; Tamul et al., 2020). The ASIS's theoretical validity was established through exploratory and confirmatory factor analyses (Sak et al., 2016). The correlations between ASIS scores and the UNIT and RIAS intelligence tests range from .50 to .82 (Sak et al., 2019). There is a significant relationship between ASIS scores and academic performance in math (.69 and .82), science (.57 and .77), social studies (.59 and .81), and language arts (.63 and .83) (Sak et al., 2019). In a separate study, test users rated the social validity of ASIS as exceptionally high (Tamul et al., 2020).

Reliability studies encompassed internal consistency, test-retest stability, and inter-rater agreement. The median test-retest reliability coefficient is 0.91 for index scores and somewhat lower for subtest scores. Test-retest correlations vary from .88 (Nonverbal) to .98 (Fluid Reasoning) for index scores and from .66 (visual-spatial memory) to .85 (visual-spatial reasoning) for subtests. The median reliability coefficient for internal consistency stands at .91 for subtest scores and .97 for index scores. The inter-rater reliability coefficient ranges between .96 and 1.00 (Tamul et al., 2020).

The ASIS was also used to assess the performance of clinical groups. The results showed that gifted children, children with autism, and children with intellectual disabilities were mostly correctly identified. Additionally, test users reported high satisfaction with the ASIS in terms of its content, administration, and interpretation (Cirik et al., 2020; Sözel et al., 2018; Tamul et al., 2020). In short, the ASIS is a reliable and valid tool for assessing the performance of clinical groups.

2.3. Procedure

The data set were obtained with formal permission from the administration office of the Research and Practice Center for High-Ability Students Education at Anadolu University, holding the copyright of the ASIS. The data was sorted and filtered to match the study's goals. The study only used the data of 386 students with a GIQ score of 130 or higher. The data set did not include the participants' names. Each individual was coded with a number.

2.4. Data Analysis

Prior to analyses data set restricted with gifted ones who get 130 and above score at GIQ. Then data were screened for missing values, and normal distribution. There were no missing values in data set. When considering the visual examination of histograms and box plots, and skewness and kurtosis values (See Table 2).) it has been determined that all variables exhibit a normal distribution (Demir, 2022; Mayers, 2013).

In order to determine the cognitive profiles of gifted students, a statistical technique called latent profile analysis (LPA) was utilized. LPA is a method that identifies distinct groups, known as latent profiles, within a population based on continuous variables (Harring & Hodis, 2016). The analysis involved applying LPA to the data collected from all participants using the 7 subtests of ASIS, using a package called tidyLPA in R. The tidyLPA package allows for the specification of different models that estimate various parameters such as means, variances, and covariances (Rosenberg et al., 2018). It also enables the comparison of different solutions based on the number of profiles extracted. In this study, models with one and six profiles were tested to determine the optimal number of profiles. To evaluate the goodness of fit of the models, several criteria were used: the Akaike Information Criterion [AIC], Approximate Weight of Evidence [AWE], Bayesian Information Criterion [BIC], Classification Likelihood Criterion [CLC], and Kullback Information Criterion [KIC]. Lower values of these criteria indicate better model fit (Ferguson et al., 2020). The best fit between the models was determined using the bootstrapped likelihood ratio test [BLRT]. Additionally, the entropy values of the models were examined, with an entropy value above 0.8

indicating a good fit (Tein et al., 2013). Finally, the criterion that the smallest profile should not account for less than 5% of the sample was taken into consideration (Marsh et al., 2009).

3. Results

As illustrated in Table 2, mean GIQ, Index scores and subtest scores for this sample of gifted students were considerably above the normative mean. Their mean general intelligence (GIQ) was found to be 137.95 which is over the traditional cutoff score "130 IQ" for giftedness. Their scores ranged from 130 to 156, with a standard deviation of 7.207, which is lower than the standard deviation of the norm group (SD = 15). This finding shows that the sample is rather homogenous in terms of general intelligence, with most scores falling within a relatively narrow range around the mean. On the other hand, the verbal IQ and nonverbal IQ scores seems relatively in a wide range.

Table 2
Descriptive and Normality Statistics of ASIS Scores

	Minimum	*Maximum*	*Mean*	*SD*	*Skewness*	*Kurtosis*
Indexes*						
GIQ	130	156	137.95	7.207	.782	−.505
Verbal IQ	107	160	130.94	10.855	.360	−.116
Nonverbal IQ	111	157	135.05	9.511	.322	−.303
Subtests**						
VOC	20	86	64.35	7.746	−.188	2.304
VAR	51	91	71.05	8.370	.400	.187
VSTM	35	91	63.47	9.301	.261	.418
VSAR	51	91	70.09	7.164	.311	.645
VPF	38	91	68.59	10.346	.139	−.032
VPM	40	91	63.16	8.949	−.207	.625
VSPM	38	91	64.21	8.339	.253	.387

Note. *IQ scores; ***t* scores; VOC: Vocabulary; VAR: verbal analogies; VSAR: Visual-spatial reasoning; VPF: Visual flexibility; VSTM: Verbal short-term memory; VPM: Visual pattern memory; VSPM: Visual sequential processing memory.

The Verbal IQ statistics shows that some individuals scoring relatively low and others scoring relatively high. The Nonverbal IQ scores range from 111 to 157, with a mean of 135.05 and a standard deviation of 9.511. This suggests that the sample of individuals being measured has a relatively high level of nonverbal intelligence, with most scores falling within a relatively narrow range around the mean. Subtest-level analyses showed that gifted students had the highest mean score on the Verbal Analogies Subtest (M = 71.05), followed by visual-Spatial Reasoning Subtest (M = 70.09). They get the lowest score at the Visual Pattern Memory Subtest (M= 63.16) and at the Verbal Short-Term Memory Subtest (M = 63.47). Bivariate correlations among the study variables are provided in Table 3.

All of the variables except VSPM have a significant correlation with at least one variable. The largest positive significant correlation is seen between VOC and VAR (r=.310). on the other hand, the largest negative significant correlation is seen between VOC and VPF (r=-.238).

After the data set was prepared for profile analysis, LPA was conducted to find covert profiles of the gifted sample. The ability to unveil the hidden categories within a latent profile model is significantly influenced by the chosen technique or benchmark that guides the classification process. Despite informed suggestions and simulation studies, there is no common standard for the best fit criteria and researchers typically use a combination of fit criteria in determining the number of latent classes (as cited in Tein et al., 2013). Table 4 showcases the model fit indices for a variety of LPA solutions.

Table 3
Bivariate Correlations Among Subtests

Subtest	1	2	3	4	5	6
1.VSPM	–					
2.VAR	−.100	–				
3.VPF	.027	−.134**	–			
4.VSAR	−.022	.065	.068	–		
5.VSTM	−.083	.194**	−.169**	−.064	–	
6.VPM	.073	−.080	.008	.080	−.174**	–
7.VOC	−.077	.310**	−.238**	−.107*	.148**	−.112*

Note. **. Correlation is significant at the 0.01 level (2-tailed). *. Correlation is significant at the 0.05 level (2-tailed). VSPM: Visual sequential processing memory; VAR: Verbal analogies; VSAR: Visual-spatial reasoning; VPF: Visual flexibility; VSTM: Verbal short-term memory; VPM: Visual pattern memory; VOC: Vocabulary.

Table 4
Comparison of model fit criteria

Profiles	*AIC*	*BIC*	*AWE*	*CLC*	*KIC*	*Entropy*	*BLRT p-value*
1	19284.381	19339.763	19463.145	19258.381	19301.381	-	-
2	19207.812	19294.841*	19490.870*	19164.811	19232.812	0.50	0.01*
3	19192.599	19311.274	19578.831	19133.717	19225.599	0.55	0.01
4	19189.997	19340.319	19679.463	19115.175	19230.997	0.58	0.01
5	19174.944	19356.913	19767.687	19084.139	19223.944	0.59	0.01
6	19157.104*	19370.720	19853.069	19050.371*	19214.104*	0.63*	0.01

Note. *lowest values

Utilizing an analytic hierarchy process that takes into account AIC, AWE, BIC, CLC, and KIC fit indices (Akogul & Erisoglu, 2017), the 2 class model is identified as the most suitable LPA solution. Although the fit indices proposed alternative models, the 2 class model was ultimately chosen due to its low BIC value and favorable BLRT test outcome. While the 6-class LPA solution had a lower AIC and a greater entropy value, there were more overlaps in the resulting means (i.e. classifications were less discriminating) and the final class sizes fell below the recommended threshold. Moreover, studies show that BIC and BLRT are more reliable fit indices than AIC and entropy for selecting the number of classes (Tein et al., 2013). As a result, we selected the two-class solution as the best representation of the most likely class membership for our study participants.

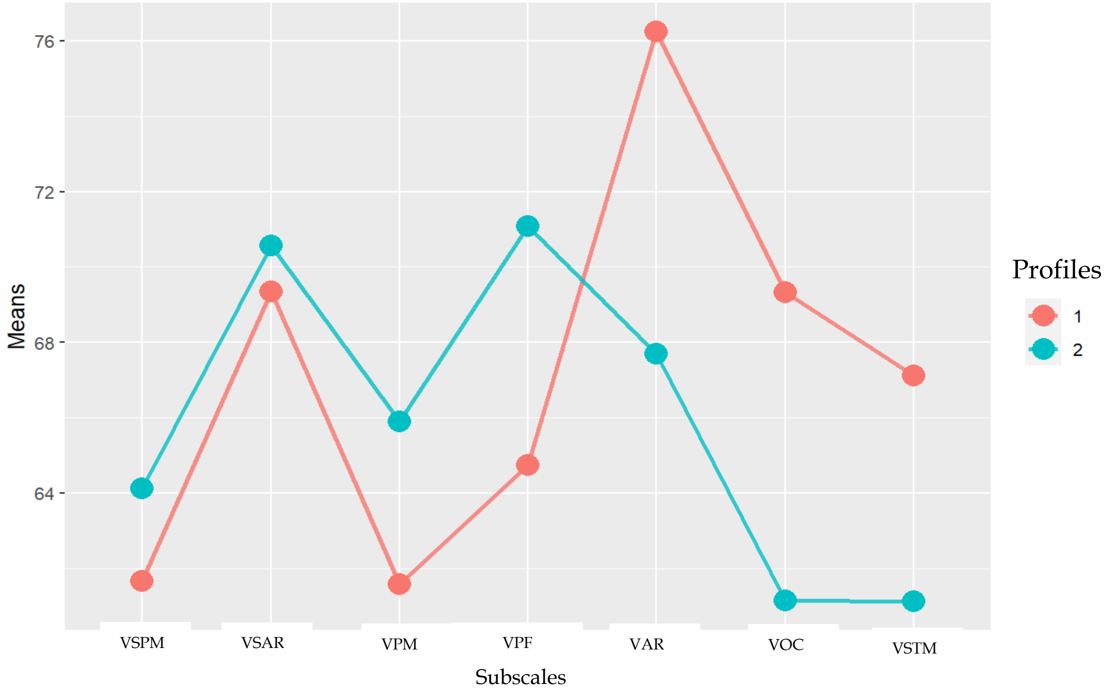
Table 5
Means and standard deviations for profiles

Variables	*Verbal Gifted (n=146)*	*NonVerbal Gifted (n=240)*
Verbal analogies	77.32 (7.78)	67.23 (6.12)
Verbal short-term memory	67.39 (9.07)	61.08 (8.62)
Vocabulary	70.49 (6.19)	60.62 (6.03)
Visual sequential processing memory	61.92 (8.97)	63.90 (8.87)
Visual-spatial reasoning	69.40 (7.59)	70.50 (6.87)
Visual flexibility	64.05 (9.94)	71.35 (9.60)
Visual pattern memory	61.22 (8.46)	66.03 (7.73)

Table 5 and Figure 2 display the class names and their respective descriptive statistics. Two profiles emerged from the data, termed as Verbal Gifted and NonVerbal Gifted. As per Table 5, both these groups exhibit higher average scores across all subtests than norm group average scores (50). The Verbal Gifted profile, comprising 38% of the students (N=146), demonstrated better performance on verbal subtests (VAR, VSTM, VOC) than nonverbal ones (VSPM, VSAR, VPF, VPM). The group members get the highest scores on VAR subtest (77.32) and the lowest scores on

VSPM (61.92) and VPM (61.22) subtests. Conversely, the NonVerbal Gifted profile, which accounted for about 62% of the students (N=240), was characterized by its members' elevated scores on nonverbal subtests compared to verbal ones. They get the highest scores on VPF (71.35) and VSR (70.50) while the lowest scores on VOC (60.62) and VSTM (61.08) subtests.

Figure 2
Two-Profile Model



Note; Profile 1=Verbal Gifted, Profile 2= NonVerbal Gifted

4. Discussion and Conclusion

The study aimed to create cognitive profiles of gifted students with an IQ of 130 and above who were identified with ASIS. This was achieved by conducting latent profile analysis (LPA) using scores obtained from 7 subtests. During the analysis phase, an analytical hierarchy process was employed, considering fit indices such as AIC, AWE, BIC, CLC, and KIC (Akogul & Erisoglu, 2017). Based on these indices, the 2-class model was identified as the most suitable LPA solution. Consequently, a two-class solution was selected to represent the participants' class membership, resulting in the emergence of two profiles: Verbal Gifted and NonVerbal Gifted. Both groups of students demonstrated higher mean scores in all subtests compared to the norm group mean of 50. This indicates that the gifted students with ASIS possessed superior cognitive abilities across various domains, regardless of their specific profile. This outcome is not surprising, as gifted individuals are recognized for their advanced abilities and tend to excel on intelligence tests (McGrew et al., 2014; Roid, 2003; Sak et al., 2019). Furthermore, this finding underscores the ASIS as a reliable tool for evaluating highly capable children. However, in another study utilizing the ASIS, Sak et al. (2019) obtained similar results, with gifted students achieving above-average scores in all subtests.

Out of the total number of students, the verbal gifted profile consisted of 38% (N=146) of the participants. This group exhibited superior performance on the verbal subtests, namely VAR (verbal analogies), VSTM (verbal short-term memory), and VOC (vocabulary), compared to the non-verbal subtests, which included VSPM (visual sequential processing memory), VSAR (visual flexibility), VPF (visual flexibility), and VPM (visual pattern memory). Specifically, members of the Verbal Ability group achieved the highest mean score on the VAR subtest, with a score of 77.32. Conversely, their lowest mean scores were observed in the VSPM and VPM subtests, with scores of 61.92 and 61.22, respectively. These results indicate that the verbal gifted profile excelled in tasks involving verbal reasoning, analogies, and linguistic abilities, while their performance in tasks requiring visual sequential processing and visual pattern memory was comparatively lower.

On the other hand, around 62% (N=240) of the students were classified under the NonVerbal Gifted profile. This group demonstrated stronger performance on the nonverbal subtests in comparison to the verbal subtests. Notably, members of this profile achieved the highest mean scores on the VPF (visual flexibility) and VSAR (visual sequential processing memory) subtests, with scores of 71.35 and 70.50, respectively. Conversely, their lowest mean scores were observed in the VOC (vocabulary) and VSTM (verbal short-term memory) subtests, with scores of 60.62 and 61.08, respectively. These findings indicate that the NonVerbal Gifted profile excelled in tasks involving visual flexibility and sequential processing, while their performance in tasks requiring verbal skills and vocabulary was comparatively lower.

This study's most significant contribution lies in its empirical support for acknowledging the cognitive differences and diversity among gifted individuals with a heterogeneous structure. By challenging the notion of a single profile for general intelligence, this research highlights the importance of considering multiple domains and psychometric categories when identifying and supporting gifted individuals. It is crucial to recognize that presenting a singular profile for general intelligence can impose limitations and biases when identifying gifted individuals across various domains and providing appropriate support (Treffinger, 1982). Moreover, Worrel (2009) emphasizes the necessity for research that challenges this notion, aiming to move away from relying solely on a single score for identifying gifted individuals. Furthermore, existing literature on the subject supports this notion, with studies focusing on uncovering the profiles of gifted students within different psychometric categories.

For instance, the study conducted by Liratni and Pry (2012) specifically focused on the interpretability of total IQ and the potential heterogeneity among scores. They analyzed the psychometric profiles of 60 gifted children, aged 6 to 13, using the WISC IV intelligence scale. The findings revealed a significant variation in the profiles, leading to the total IQ of 87% of the children being difficult to interpret. Interestingly, 77% of the children displayed a Verbal Index that exceeded other indices, indicating a particular strength in verbal abilities. Furthermore, in another study by Castejon et al. (2016), four different profiles of giftedness were identified: general mental ability, differential aptitudes, creativity, and academic achievement. These profiles provided a comprehensive understanding of the diverse strengths and abilities exhibited by gifted students in different domains. However, the findings of our research also suggest that there are different cognitive strengths and weaknesses among students with different profiles. The Verbal Gifted profile excels in verbal abilities but struggles with visual processing tasks, while the NonVerbal Gifted profile excels in visual processing but faces challenges in verbal tasks. Overall, these studies shed light on the complexity and diversity within the gifted population, emphasizing the importance of considering multiple factors and profiles when assessing giftedness.

In addition, there are twice exceptional individuals among gifted individuals. These students are known to have both giftedness and accompanying developmental delays such as ADHD, learning disability and autism. Therefore, especially for these individuals, results based on a single score are misleading in showing their actual performance. Especially in these groups, it is important to reveal which developmental areas are deficient in terms of educational interventions and clinical support. For instance, Guenole et al. (2015) conducted a study with gifted students who exhibited socio-emotional problems, school underachievement, or maladjustment. The researchers administered the WISC-III to assess the students. The results revealed significant differences in verbal and visual performance scores among the participants.

Moreover, the findings from Cirik et al.'s (2023) study shed light on the complexity of learning disabilities and the limitations of relying on a single measure to understand them. By employing latent profile analyses, the researchers identified three distinct profiles among the participants: the zigzag profile, the wavy profile, and the waterfall profile. Each profile represented a unique pattern of strengths and weaknesses in cognitive abilities. However, the one common weakness shared by all three profiles was in visual sequential processing memory. These findings suggest that difficulties in visual sequential processing memory may play a role in the development of learning disabilities. Likewise, these findings highlight the importance of considering multiple cognitive factors and profiles when assessing and understanding learning disabilities, rather than relying solely on a single score or measure.

Lastly, the underrepresentation of students from diverse cultural backgrounds is a significant issue in gifted education. Hodges et al. (2018) conducted a meta-analysis of 54 studies to investigate this underrepresentation. The researchers argue that the limited representation of black, Hispanic, and Native American students can be attributed to the use of traditional diagnostic methods, such as IQ scores and standardized achievement tests based on total scores. While non-traditional methods (e.g. profile analysis) may help identify more underrepresented students as gifted, the findings of this meta-analysis highlight the need for improved diagnostic methods to address inequalities in identification.

The assessment is the first step in an educational program, and by conducting research to explore the cognitive profiles of gifted students, we have the potential to improve the representation of students from diverse cultural backgrounds in gifted programs. This study's strength lies in providing empirical evidence for the diversity within the gifted student population and identifying distinct characteristics. These findings allow for the development of targeted educational interventions that cater to the diverse nature of giftedness (Tommis & Phillipson, 2013). For example, offering content-based educational activities tailored to verbal materials for verbally gifted students and visual materials for visually gifted students can enhance their interests and abilities. Consequently, students identified based on their cognitive profiles can be directed towards relevant areas, enabling differentiation of educational content. Engaging in research on various cognitive profiles presents opportunities for comprehensive and detailed analyses, ultimately contributing to a more equitable and inclusive gifted education system. Additionally, by recognizing and valuing the diverse cognitive profiles of gifted students, educators can provide personalized educational experiences that foster their intellectual growth and maximize their potential.

In conclusion, this study successfully created cognitive profiles of gifted students with an IQ of 130 and above who were identified with ASIS. Through latent profile analysis, two distinct profiles emerged: Verbal Gifted and NonVerbal Gifted. Both groups demonstrated superior cognitive abilities across various domains compared to the norm group mean. These findings challenge the notion of a single profile for general intelligence and emphasize the importance of considering multiple domains and psychometric categories when identifying and supporting gifted individuals. By recognizing and valuing the diverse cognitive profiles of gifted students, educators can provide tailored interventions and support systems that promote equitable and inclusive gifted education. Overall, this research contributes to a more comprehensive understanding of giftedness and paves the way for targeted educational interventions that cater to the unique strengths and needs of gifted students.

5. Limitations and Suggestions

Finally, while this study provides valuable insights into the cognitive profiles of gifted students with ASIS, there are several limitations that should be acknowledged. Since it is still widely accepted as a common entry point for many gifted education programs that use intelligence tests as the basic identification tool (Hunsaker, 2023; Sak et al., 2019), the study's focus on an IQ threshold of 130 and above as the criteria for giftedness may restrict the applicability of the findings to a broader population of gifted individuals. Additionally, the study employed latent profile analysis to identify two distinct profiles, but it is important to note that the choice of a two-class solution may not fully capture the complexity and diversity within the gifted population. Lastly, the study did not explore potential interactions between cognitive profiles and other factors such as socio-economic status or cultural background, which may influence the manifestation of giftedness. Future research should address these limitations to further enhance our understanding of the cognitive profiles of gifted individuals and inform effective educational practices.

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