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Exploring cognitive patterns in children with autism spectrum disorder using correlation and cluster analysis

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ABSTRACT

This paper investigates the relationships between age and five cognitive abilities in children diagnosed with autism spectrum disorder (ASD). Data from 210 children aged 6 to 12 years who completed measures of visual motor precision (VM), facial memory (FM), spatial vision (SV), drawing memory (DM), and orientation (OR) were analyzed. Data preparation, descriptive statistical analysis, correlation analysis, cluster analysis, and factor analysis were conducted. The results showed that age was not significantly associated with the cognitive measures. The clearest association was a moderate positive correlation between VM and FM (0.34). Cluster analysis identified three groups. However, the low silhouette score (0.1368) indicated weak separation and substantial overlap between cognitive profiles. Factor analysis suggested three latent dimensions: factor 1 was strongly associated with VM and FM; factor 2 was negatively related to DM and moderately positively related to OR; and factor 3 was primarily driven by SV. These findings suggest that cognitive abilities in children with ASD operate relatively independently, with some shared mechanisms between certain skills. It can be concluded that individualized approaches in assessment and intervention strategies are warranted.

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1. INTRODUCTION

Cognitive variability is a core feature of autism spectrum disorder (ASD), a neuro-developmental condition characterized by challenges in social interaction, communication, and repetitive behaviors. Children with ASD often exhibit wide-ranging differences in cognitive abilities, impacting learning, and daily functioning. Key cognitive abilities, including visual motor precision (VM), facial memory (FM) [1], spatial vision (SV) [2], drawing memory (DM) [3], and orientation (OR) [4], play crucial roles in a child's capacity to engage with and comprehend their surroundings. Understanding the relationships between these cognitive skills could identify developmental needs of children with ASD and facilitate the design of targeted intervention and educational strategies [5].

VM refers to the coordination of visual perception and motor action, for example, during writing, tracing, or drawing. Difficulties in VM may interfere with tasks that require hand-eye coordination and fine motor control. FM refers to the ability to recognize and remember faces and is closely linked to social interaction. Difficulties in FM may contribute to challenges in recognizing people and interpreting social cues.

SV refers to the ability to perceive spatial relations between objects and the self, which is needed for navigation and understanding spatial environments. DM measures the ability to recall and reproduce visual forms or patterns, reflecting visual memory and visual processing. OR refers to spatial awareness and the ability to locate oneself or objects accurately in space. Together, these abilities provide a useful profile of cognitive functioning in children with ASD.

Previous research suggests that cognitive abilities in ASD are heterogeneous, with children showing different patterns of strengths and weaknesses across domains [6], [7]. However, the relationships between these abilities remain unclear. It is not yet clear whether stronger performance in one cognitive domain is associated with stronger performance in another, or whether these domains develop largely independently. Therefore, this study examined the correlations between age, VM, FM, SV, DM, and OR in a sample of 210 children with ASD aged 6 to 12 years. This age range was selected because it represents an important developmental period during which cognitive abilities are actively shaping learning, communication, and adaptive functioning. To examine the relationships between the cognitive measures, this study extends the previous results [8] and use Pearson and Spearman correlation matrices to assess both linear and rank-based relationships between age and the five cognitive variables. This approach allowed us to determine whether specific abilities tended to co-vary, and whether age was associated with cognitive performance within the sample. Identifying such associations is important because related abilities may share underlying mechanisms or may improve together during intervention.

This study then used K-means cluster analysis to examine whether children with ASD could be grouped according to their cognitive performance across age, VM, FM, SV, DM, and OR. This method partitions cases into groups according to similarity across the selected variables and can reveal possible cognitive profiles. The dataset showed variation across the five cognitive domains. Clustering quality was evaluated using the silhouette score, which reflects how well each child fits within the assigned cluster compared with other clusters. Cluster distribution was visualized using principal component analysis (PCA) to reduce dimensionality. Additionally, factor analysis was conducted to explore relationships between cognitive variables, with the aim of providing a comprehensive understanding of cognitive abilities and their correlations in children with ASD. The findings could inform the development of targeted interventions that address specific cognitive strengths and weaknesses, ultimately enhancing educational outcomes and capabilities for children on the autism spectrum.

2. RELATED WORK

There has been increasing interest in studying several aspects of ASD using artificial intelligence (AI) methods. Various AI applications and algorithms have been utilized to address challenges faced by individuals with ASD, including early diagnosis, assessment, personalized interventions, support, and educational methods. A comprehensive analysis by Salamanca *et al.* [9] examined executive function (EF) profiles in children with ASD, revealing significant deficits across multiple EF domains. The children demonstrated difficulties in cognitive flexibility and planning. These findings highlight the need for targeted interventions aimed at improving EF skills in children with ASD.

In the area of visual-spatial processing, there is evidence that children with ASD may utilize alternative strategies for processing visual-spatial information. Mouga *et al.* [10] used advanced eye-tracking technology to gain insights into how children with ASD perceive and interpret spatial information. Their study uncovered atypical gaze patterns during spatial tasks, suggesting that these children may draw on different cognitive resources when processing spatial relationships compared with typically developing peers. This research has important implications for the development of educational materials tailored to leverage the visual-spatial processing abilities observed in children with ASD.

Social cognition, a key area of difficulty in ASD, was focus of a longitudinal study [11]. Over a five-year period, they tracked the development of social cognitive skills in children with ASD. While they observed improvements in these skills over time, the rate of progress was slower compared to typically developing peers, with theory of mind abilities showing the most significant lag. These findings are consistent with previous research reporting social cognitive differences in autism [12], and emphasize the importance of early and sustained interventions targeting social cognitive skills in ASD.

Several studies have explored various aspects of cognitive and behavioral profiles in individuals with ASD. Vries *et al.* [13] conducted a randomized controlled trial to evaluate the efficacy of cognitive flexibility training in individuals with ASD. The study aimed to improve this critical EF in ASD participants, and the research assessed the impact of targeted interventions on cognitive flexibility, a skill often found to be challenging for individuals with ASD. Gabrielsen *et al.* [14] utilized cluster analysis to investigate visual cognitive styles in autism, potentially identifying subgroups according to visual processing characteristics, brain imaging techniques were employed to investigate neural mechanisms associated with language difficulties in this subgroup. The study demonstrated that language processing in these children differs from typical neural processing patterns.

Brigido *et al.* [15] also utilized cluster analysis, focusing on behavioral profiles in ASD in order to identify distinct behavioral subgroups within the autism spectrum. Rosello *et al.* [16] conducted a longitudinal study examining executive and socio-adaptive behaviors in adolescents with ASD without intellectual disability. Tracking the development of these skills over time and identifying distinct subgroups within this ASD population, the study shows how EF and social adaptation skills evolve during adolescence in different ASD subgroups, potentially informing more tailored interventions and support strategies. Table 1 shows a summary of research studies on ASD.

Table 1. Summary of research studies on ASD

Ref.	Study focus	Methods and tools	Benefits	Limitations
[17]	Educational support for children with ASD	Cognitive computing machine learning (ML)	Personalized learning and adaptive assistance	Limited scalability, bias, and development intensive
[12]	Perception enhancement	ML and wearable sensors robotic systems	Improved perception and social interaction	Cost, discomfort, and limited accessibility
[18]	Early diagnosis and screening	ML data mining	Accurate assessment and early intervention	Lack of specificity
[19]	Healthcare applications	AI and data analysis	Enhanced healthcare management and personalized treatment	Data constraints and potential for privacy concerns
[20]	Screening and early detection	AI algorithms and data analysis	Efficient screening and early intervention	Limited scope and validation needed
[21]	Classification and detection	Deep learning	Accurate and early identification	Requires large datasets
[22]	ASD diagnosis	ML correlation filters	Diagnostic accuracy and personalized treatment	Limited and Feature-dependent
[23]	Face response classification	ML neuroimaging	Identification of neural abnormalities and early diagnosis	Expensive, time-consuming, and limited accessibility
[24]	Functional connections	ML optimization and neuroimaging	Brain network abnormalities and personalized treatment	Expensive, time-consuming, and visual-specific
[15]	Behavioral profiles in ASD	Cluster analysis	distinct subgroups within ASD	Cannot capture all ASD dimensions
[25]	Visual cognitive styles in ASD	Cluster analysis	Visual processing patterns	Limited to visual cognition
[26]	Gesture skills in ASD	Cluster analysis	Gesture skill-based subgroups	Focuses on Chinese autistic children
[16]	Executive behaviors	Statistical analysis	Executive, socio-adaptive behaviors	Children without intellectual disability
[27]	Diagnosis and assessment	Fuzzy cognitive maps modeling software	Improved diagnostic accuracy	Limited generalization and potential for overfitting
[10]	Visual-spatial process	Eye-tracking and AI	Processing insights	Eye-tracking only
[11]	Social cognition in ASD	Statistical analysis	Long-term insights	Non-AI approach and limited scope
[28]	Electroencephalogram (EEG) ASD prediction	Deep learning and convolutional neural network (CNN)	Early detection	EEG-dependent
[29]	Emotion recognition	Computer vision and ML	Improve social interaction	Facial expression focus
[30]	ASD traits classification	Natural language processing (NLP) and transformer models	Language-based insights	Text data reliance

According to Table 1, these studies across different cognitive domains indicate that understanding cognitive skills in children with ASD involves various levels and types of assessment depending on the specific features of each cognitive profile. It seems that each child's cognitive and developmental characteristics are reflected in the patterns of their abilities, and naturally, the most prominent analytical methods should be chosen for assessment and classification. This literature analysis showed that understanding and measuring the cognitive abilities in children with ASD is complex and not straightforward. AI algorithms can be useful in identifying correlations between cognitive abilities in children with ASD beyond traditional statistical methods. In addition, advanced methods, such as clustering and factor analysis, can be effective in grouping profiles within the ASD data, and hence, define more accurate correlations. Deep learning can also be useful when large datasets are available [31], [32]. This approach can help advance our understanding of ASD abilities, which will have impact on how to handle these situations at earlier stages.

3. METHOD

This study aimed to examine the relationships between cognitive abilities in children with ASD. A structured statistical procedure was used to describe the data, examine associations between variables, and explore whether the cognitive measures formed meaningful subgroups or underlying dimensions. The procedure included: i) data preparation to ensure the quality and consistency of the dataset, ii) descriptive statistical analysis to characterise the main features of the variables, iii) correlation analysis to examine the relationships between age and cognitive functions, iv) cluster analysis to identify possible subgroups within the sample, and v) factor analysis to investigate latent cognitive structures in the studied population. This approach was used to provide an account of cognitive functioning in children with ASD, while allowing for both common patterns across the sample and individual differences in cognitive profiles.

3.1. Data preparation

The dataset included 210 children aged 6 to 12 years. Six variables were included in the analysis: age, VM, FM, SV, DM, and OR. Children's performance was assessed through five cognitive tasks measuring VM, FM, SV, DM, and OR. Scores for each cognitive skill ranged from 1 to 20, with higher values indicating stronger performance on the corresponding task. As shown in Table 2, participant 1, aged 8.2 years, scored 6 in VM, 7 in FM, 11 in SV, 13 in DM, and 4 in OR. Participant 2, aged 7.8 years, scored higher in VM (8), but lower in FM (4), compared with participant 1. Participant 3, aged 7.0 years, showed relatively consistent scores across VM, FM, and SV, with values of 5, 6, and 6, respectively, while showing higher scores in DM (14) and OR (8). These examples illustrate the variability in cognitive performance across participants and across cognitive domains. The collected data were therefore suitable for examining patterns of cognitive performance across age and skill areas. Table 2 presents a sample of the dataset.

Table 2. Cognitive skill measurements for participants

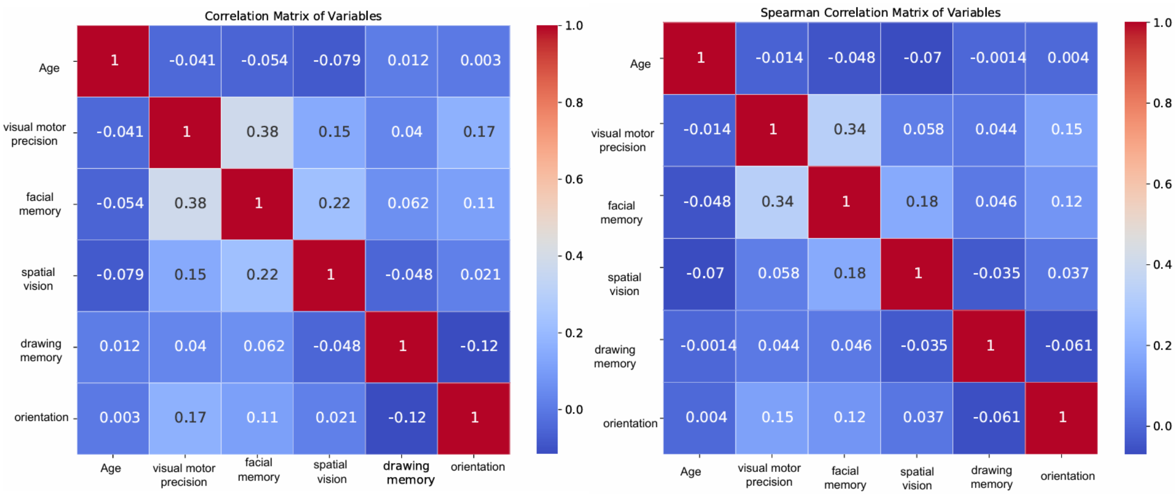
Seq.	Age	VM	FM	SV	DM	OR
1	8.2	6	7	11	13	4
2	7.8	8	4	6	13	7
3	7.0	5	6	6	14	8
4	7.6	8	11	11	12	8
5	8.5	6	9	12	6	8
6	12	6	5	5	5	9

3.2. Descriptive statistical analysis

Descriptive statistics were calculated to provide an initial characterization of the sample and the distribution of the cognitive scores. For each variable, the mean, standard deviation, minimum, maximum, and the 25th, 50th, and 75th percentiles were calculated. These statistics were used to describe the central tendency and variability of the data before conducting further analyses. This step allowed us to identify whether children tended to score higher or lower in specific cognitive domains and whether some variables showed greater dispersion than others. For example, VM showed the widest range of scores, while FM and DM showed moderate variability. This pattern suggested that the sample contained considerable heterogeneity in cognitive abilities, which supported the need for additional correlation, clustering, and factor analyses.

3.3. Correlation analysis

Following the descriptive analysis, a correlation matrix was constructed to examine the relationships between the six variables. Figure 1 shows the two types of correlation were used: Pearson correlation for linear relationships (Figure 1(a)) and Spearman correlation for rank-based (monotonic) relationships (Figure 1(b)). Pearson correlation measure was applied to detect the strength and direction of linear relationships between variables. The correlation coefficient ranges from -1 (perfect negative correlation) to 1 (perfect positive correlation), with values close to 0 indicating little to no linear relationship. For this study, Pearson correlations were used to assess how well one cognitive ability can affect another. On the other hand, Spearman correlation is useful for datasets that include ordinal or rank-based data. Spearman correlation was applied as a non-parametric alternative to Pearson. Spearman correlations measure how well the relationship between two variables can be described using a monotonic function, without assuming a linear relationship. The correlation matrices provided insights into whether certain cognitive abilities were related. For instance, this study explored whether children who scored higher in VM also performed well in FM or whether age influenced performance in specific cognitive domains.



(a) (b)

Figure 1. Correlation matrices for all variables of (a) Pearson and (b) Spearman

3.4. Cluster analysis

Next, cluster analysis was performed to group the children into distinct clusters based on their cognitive abilities. PCA is used to process variables and K-means algorithm then partitions the dataset into k clusters, where k is a predefined number of groups, and each child is assigned to the cluster with the nearest mean. K-means algorithm is used to create clusters. This algorithm seeks to minimize the within-cluster variance by adjusting cluster centroids iteratively as illustrated in Figure 2.

- Cluster selection: a key part of the K-means process is determining the appropriate number of clusters. This study initially set $k = 3$, suggesting that children with ASD might be grouped into clusters of high, moderate, and low performance across cognitive domains. Cluster validity was then examined using the silhouette score, which evaluates the quality of clustering by measuring how similar each data point is to its own cluster compared to other clusters. Scores close to 1 indicate well-defined clusters, whereas scores near 0 indicate overlap between clusters.
- Cluster characterization: after clustering, the mean values of the six variables within each cluster were examined to characterize the cognitive profiles of children in each group. This can show if children in certain clusters tended to have high performance in specific cognitive areas, or displayed more generalized tendency across different domains, for instance stronger or weaker correlation.

3.5. Factor analysis

Factor analysis is a variables reduction method that combines correlated variables together into factors, in order to provide more focus on how these variables together influence the outcomes. For factor extraction, PCA was applied for identifying potential factors where variables are expected to be correlated. Then, after the factors were extracted, rotation method was applied to clarify which variables contribute the most to each factor. Finally, factor loadings, which represent the correlations between the original variables and the extracted factors, were used to define the cognitive structures. For instance, a high loading of VM and FM on the same factor indicates that these two abilities tend to correlate. The methodology involved a multi-step process designed to capture the relationships between cognitive variables. The results of the correlation, clustering, and factor analysis were used to provide the degree of linear and rank-based relationships between the cognitive abilities. While cluster analysis can fit cognitive profiles within the dataset into groups, factor analysis can uncover hidden cognitive dimensions that could explain how these abilities were related or distinct.

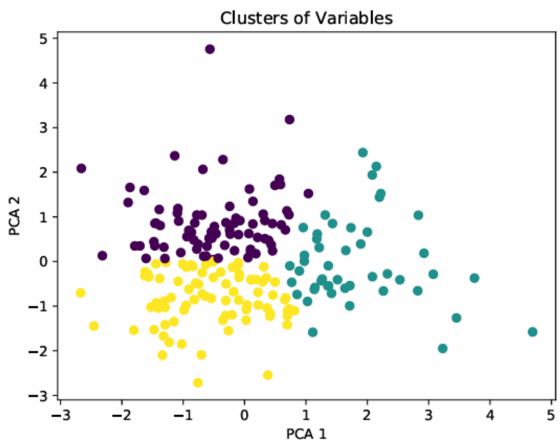


Figure 2. Clusters of variables using PCA and K-means

4. RESULTS AND ANALYSIS

The general statistics provided information about the cognitive abilities of the children. The average age was approximately 9.14 years, with a standard deviation of 1.32. The cognitive measures for all five abilities under test showed mean scores generally in the "at risk" range of scores between 8 and 12. VM had the widest range of scores, from 2 to 19, while other variables showed moderate variability. In the first step, a correlation matrix analysis was conducted, which revealed weak relationships between most variables, as shown in Figure 1. Age did not significantly correlate with any cognitive measures, suggesting that within this age group, age was not a strong predictor of performance on the assessed tasks. A moderate positive correlation between VM and FM (0.34) indicated that children who performed better in visual motor tasks tended to score higher in FM. A weak negative correlation emerged between DM and OR (-0.19), pointing to a slight inverse relationship between these abilities.

The most notable relationship observed was a moderate positive correlation (0.34) between VM and FM, suggesting that these skills may share some underlying cognitive mechanisms. Age showed negligible correlations with all cognitive measures, indicating that it did not significantly influence performance on these tasks in this dataset. SV demonstrated a moderate positive correlation (0.183) with FM, while other correlations between variables were generally weak or negligible. DM appeared largely independent of other cognitive abilities, with very weak correlations across the board. Taken together, the analysis suggests that while some cognitive tasks such as VM and FM may be somewhat related, most of the measured abilities operate with relative independence from each other.

A cluster analysis was conducted, which grouped the data into three clusters, with the largest cluster having 78 data points and the smallest having 61. However, the silhouette score was low (0.1368), indicating poor separation between clusters. This suggests that the variables used, namely age, VM, FM, SV, DM, and OR, may not clearly distinguish the groups. The weak correlations within clusters, coupled with the low silhouette score, imply potential overlap in cognitive profiles among children across different clusters, mainly in terms of linear correlation. Figure 3 shows correlation between all variables for cluster 0. There are some small positive correlations between variables, such as between age and VM (0.12) and between FM and DM (0.20). However, these correlations are generally weak. SV and OR show notable negative correlations with other variables, such as -0.17 with age and -0.24 with SV. This indicates that as these variables increase, others tend to decrease. The heatmap indicates that there are no very strong correlations among variables within cluster 0. Most correlations are weak, with a few moderate ones. This suggests that the variables do not have strong linear relationships within this cluster.

Figure 4 also shows correlation between all variables for cluster 1. The most notable relationship is the positive correlation between age and DM (0.440), suggesting that age has a more substantial effect on DM compared to other variables. SV tends to show more significant negative correlations with VM, indicating an inverse relationship in this cluster. Other correlations are generally weak, with many values close to zero, indicating minimal relationships between those variables. Figure 5 shows correlation between all variables for cluster 2. The most notable relationship in this cluster is the positive correlation between age and DM (0.304), suggesting that age has a more significant effect on DM in this cluster. VM and SV show a moderate negative correlation, indicating an inverse relationship. Most other correlations are weak, with several variables having minimal or no significant relationships with each other.

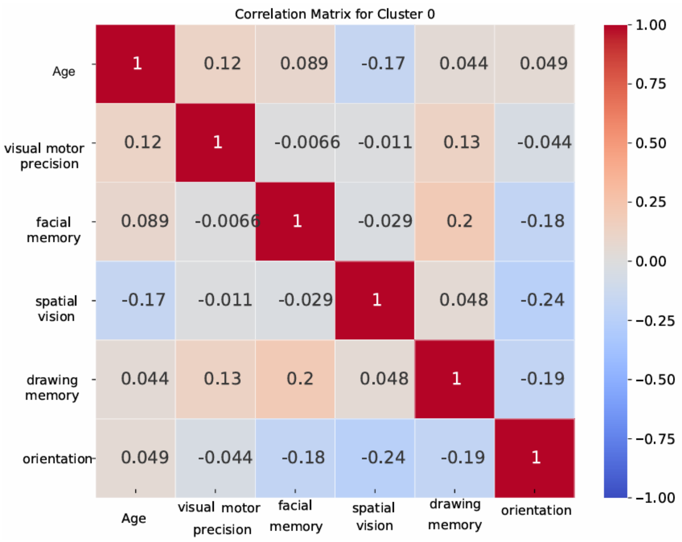


Figure 3. Correlation matrix between all variables for clusters 0

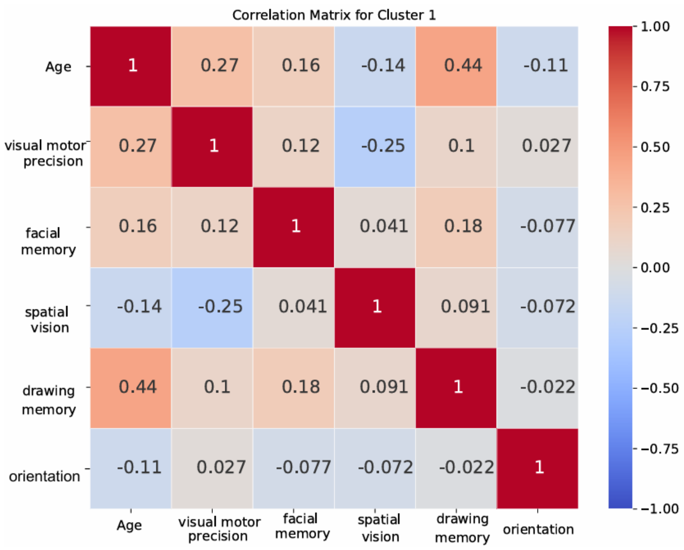


Figure 4. Correlation matrix between all variables for clusters 1

Figure 6 shows heatmap for relationships between variables and factors. VM (0.603) and FM (0.642) have strong positive loadings on factor 1, suggesting that these variables are closely related and likely contribute to this factor. SV (0.329) also has a moderate positive loading, indicating it shares some relationship with this factor but is less strongly associated. Age (-0.088) and DM (0.040) have very low loadings, suggesting they do not contribute significantly to factor 1. OR (0.235) demonstrated a weak positive loading, indicating a limited association with factor 1. Factor 1 was strongly associated with VM and FM, suggesting that these two variables represent a shared cognitive dimension.

The figure also illustrates that DM (-0.404) demonstrated a strong negative loading on factor 2, indicating an inverse relationship with this factor. OR (0.372) showed a moderate positive loading, reflecting a moderate association with factor 2. VM (0.018), FM (-0.097), and age (0.010) demonstrated very low loadings, suggesting that these variables do not significantly contribute to this factor. SV (-0.003) exhibited a negligible loading, indicating the absence of a significant relationship with factor 2. Therefore, factor 2 demonstrated a strong negative association with DM and a moderate positive association with OR, suggesting that these abilities are connected to a different cognitive dimension.

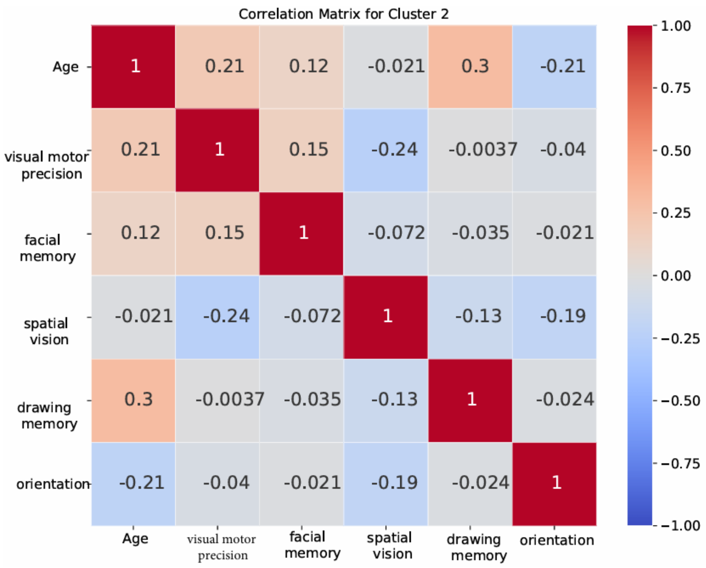


Figure 5. Correlation matrix between all variables for cluster 2

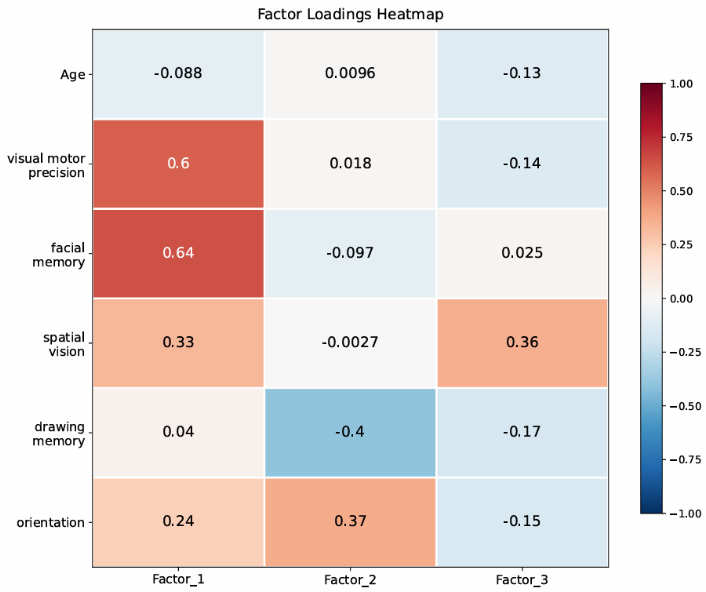


Figure 6. Relationships between variables and factors

Finally, SV (0.357) demonstrated a moderate positive loading on factor 3, indicating a notable relationship with this factor. VM (-0.142) and DM (-0.167) exhibited weak negative loadings, suggesting limited relationships with this factor, while FM (0.025) and OR (-0.153) have very weak loadings, indicating minimal contribution to factor 3. Age (-0.127) also has a very weak loading. Thus, factor 3 was mainly driven by SV, with minimal contributions from other variables. These results deserve attention because they suggest that the underlying cognitive structure is characterized by distinct dimensions, with some variables clustering together while others show contrasting relationships. It seems that each factor's cognitive composition is reflected in the development of the child's processing framework, and naturally, the most prominent dimension captures the abilities most closely associated with shared cognitive mechanisms. Figure 7 provides a comprehensive view of the data factor scores and loadings.

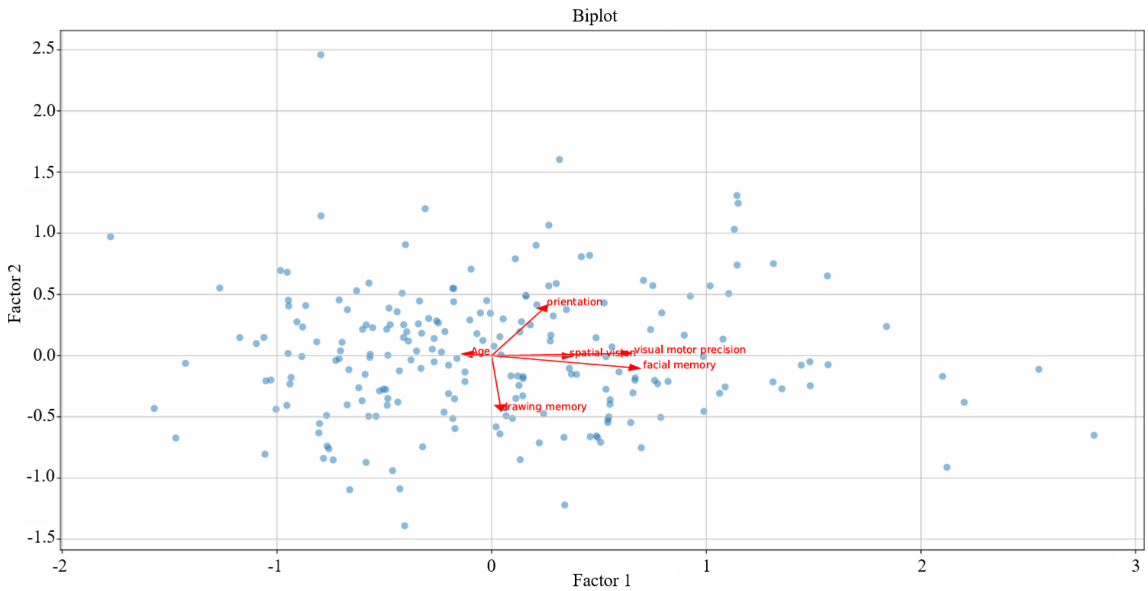


Figure 7. Comprehensive view of the data factor scores and loadings

5. DISCUSSION AND RECOMMENDATIONS

In the present analysis, weak correlations were found among most of the assessed abilities, suggesting that these cognitive domains operate with relative independence. This finding challenges the assumption that cognitive skills in children with ASD are closely connected or develop in a uniform pattern. Instead, it supports the view that cognitive development in ASD is complex, uneven, and highly individual during this important age range. The analysis of cognitive skills in children with ASD offers several practical benefits. By identifying specific cognitive profiles, interventions can be personalized and made more responsive to the child's strengths and weaknesses. Distinct patterns of cognitive functioning may also support earlier ASD identification and more timely intervention. These findings may also inform teaching strategies that are better aligned with the cognitive processing styles of children with ASD [33].

The integration of PCA-driven clustering with factor analysis in this study provides a useful framework for identifying latent cognitive structures in ASD populations. This multi-method approach allowed us to examine both possible subgroups and underlying dimensions of cognitive variability. The findings suggest potential applications in adaptive educational tools and personalised therapy plans. This may be useful because the moderate positive correlation between VM and FM suggests some shared cognitive mechanisms between these abilities. Future extensions may include AI-enhanced clustering methods that use deep learning algorithms for more sophisticated pattern recognition, longitudinal tracking systems that monitor cognitive development over extended periods, and multimodal integration of behavioral, cognitive, and neurobiological data. ML prediction models may also be developed to forecast developmental trajectories from early cognitive profiles, enabling earlier and more targeted intervention. In addition, adaptive assessment tools that adjust in real time according to a child's cognitive profile may provide more accurate and individualised evaluation.

Finally, this study intends to consider other aspects in this group of children, including attention deficit hyperactivity disorder [34].

6. CONCLUSION

This study investigated cognitive patterns in children with ASD aged 6 to 12 years using correlation analysis, cluster analysis, and factor analysis. The results showed weak correlations between most cognitive variables, and age was not significantly associated with cognitive performance. The clearest association was a moderate positive correlation (0.34) between VM and FM, suggesting possible shared underlying mechanisms. Cluster analysis identified three groups, but the low silhouette score (0.1368) indicated weak separation and substantial overlap between cognitive profiles. Factor analysis identified three dimensions: factor 1 was associated with VM and FM, factor 2 was associated with DM and OR, and factor 3 was primarily associated with SV. These findings demonstrate the heterogeneous nature of cognitive abilities in children with ASD and support the need for individualized assessment and intervention. The study contributes a framework that combines PCA-driven clustering with factor analysis for cognitive profiling in ASD. Future research should examine longitudinal developmental trajectories, AI-enhanced prediction models, broader cognitive domains, and the integration of neurobiological and environmental factors. Exploring non-linear relationships and using more sophisticated clustering techniques may reveal patterns that were not captured in the present analysis. Combining cognitive assessment with neuro-imaging may also help link cognitive profiles to underlying brain structure and function.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C	: **C**onceptualization	I	: **I**nvestigation	Vi	: **Vi**sualization
M	: **M**ethodology	R	: **R**esources	Su	: **Su**pervision
So	: **So**ftware	D	: **D**ata Curation	P	: **P**roject Administration
Va	: **Va**lidation	O	: Writing - **O**riginal Draft	Fu	: **Fu**nding Acquisition
Fo	: **Fo**rmal Analysis	E	: Writing - Review & **E**diting		

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The data that support the findings of this study are available on request from the corresponding author, [AG]. The data, which contain information that could compromise the privacy of research participants, are not publicly available due to certain restrictions.

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