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Speech Graph Analysis of Verbal Fluency in Children with Autism Spectrum Disorders

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Abstract

Background: Autism Spectrum Disorders (ASD) are a group of developmental conditions that impair social communication and often involve repetitive behaviors. Among the core features of ASD, verbal impairments are prominent. Verbal fluency tests are widely used neuropsychological tasks to assess language skills in children with ASD. Recently, speech graphs, derived from graph theory, have been employed to analyze verbal fluency performance more comprehensively.

Methods: This study aimed to compare speech graph features from phonemic and semantic verbal fluency tasks between children with ASD and typically developing (TD) peers. Participants included 25 children with ASD (ages 7–12 years; IQ 70–85 based on the Goodenough Test) from an autism school in Tabriz, and 30 age-matched TD children from regular schools. Verbal fluency was assessed using the Kormi Nouri fluency task with phonemic cues (A, N, M) and semantic categories (boy names, girl names, body parts, fruits, colors, kitchen utensils). Spoken words were represented as nodes, and temporal links between them as edges, to construct speech graphs. Standard verbal fluency scores and graph features were analyzed using independent t-tests and Mann–Whitney U tests.

Results: Children with ASD produced fewer words in both phonemic and semantic fluency tasks compared to TD children. Their speech graphs also displayed fewer nodes and edges, smaller largest connected components, lower average shortest paths and diameters, higher graph density, and reduced average total degree in comparison to TD peers.

Conclusion: Speech graph analysis offers a novel computational approach for characterizing verbal fluency deficits in children with ASD. The findings suggest potential applications for developing computer-based rehabilitation tools for individuals with speech and language impairments. Future studies may expand these approaches to other cognitive domains.

Key Words: Autism Spectrum Disorder, Speech Graph Analysis, Verbal Fluency.

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1- INTRODUCTION

The primary goal of developmental studies is to identify the natural trajectory of child and adolescent growth, and consequently, to understand the responsibilities and interventions required when deviations from this trajectory occur. Despite individual differences, children and adolescents typically follow shared developmental principles across different age stages (1). Psychology initially focused on the study of mental functions, those operations mediated by the brain. Since the establishment of psychology as an empirical science in 1879, the discipline has emphasized mental processes, which were later reframed under the broader concept of cognition. Cognition encompasses an individual's thoughts, interpretations, knowledge, and perceptions, as well as mental processes such as perception, memory, and information processing that enable learning, planning, and problem-solving (2).

Language is embedded in the human mind, but how does it develop within it? At birth, we are unable to speak or comprehend language; nevertheless, by the age of four, most children acquire fundamental vocabulary, grammar, and pronunciation of their native language. Remarkably, this developmental pattern holds for children across all linguistic and cultural backgrounds. Language acquisition involves two interrelated yet distinct psychological processes: speech production and speech comprehension (3).

Human beings appear to possess an intrinsic drive for communication, comparable in importance to the basic need for food. This communicative drive emerges early in life, as infants attempt to convey their needs to caregivers. Around the age of one, children typically begin to produce their first words. When delays in language development or difficulties in speech production occur, early intervention becomes essential to support the child's communicative abilities.

Language is the primary tool of human thought and a central vehicle of culture. It is also a major indicator of developmental progress. By the age of four, children typically comprehend the phonemes, core vocabulary, and grammatical structures of their native language. During this period, vocabulary acquisition proceeds at a remarkably rapid pace. Young children use their emerging language abilities to achieve important goals. Even before acquiring language, they demonstrate a basic understanding of their environment (4). Moreover, a four-stage model for understanding natural language, describing the processes in their natural order can be:. 1) The first stage is speech recognition, where the auditory signals of spoken language are analyzed to identify the sequence of words. 2) This is followed by syntactic analysis, during which the sequence of words is processed using grammatical knowledge to construct the sentence structure. 3) The third stage, semantic analysis, involves combining sentence structure with the meanings of individual words to generate a partial representation of the sentence's overall meaning. 4) Finally, pragmatic analysis applies contextual information, such as the time and location of the speaker and listener, to fully interpret the intended meaning of the sentence (5). Language abilities are often impaired in various developmental disorders, including pervasive developmental disorders (PDDs). PDDs refer to a group of neurodevelopmental conditions characterized by delayed and atypical development in social, language, communication, and behavioral domains (6). Among these, Autism Spectrum Disorder (ASD), which typically manifests before the age of three, has received particular attention from researchers due to its early onset and pervasive impact on development (6).

Human development is fundamentally dependent on social interaction, particularly during the middle childhood years (ages 5 to 10), when these interactions become crucial for cognitive and emotional growth. Although children may differ in developmental pace, they undergo similar mental processes that can either support or hinder their progress depending on various biological and environmental factors. Language is an intrinsic aspect of human existence, and communication occurs through both verbal and nonverbal behavior. Through complex processes of interpretation and decoding, individuals can understand the messages others are attempting to convey. While language is learned through social interaction, humans are born with an innate capacity for language acquisition. Although children with ASD may utilize alternative communication systems, they acquire language through the same fundamental mechanisms as typically developing children (7).

According to the American Psychiatric Association (APA), autism is a neurodevelopmental disorder characterized by impairments in social-communicative skills and the presence of restricted, repetitive behaviors. Clinically, the term ASD is now preferred, as the condition manifests across a range of symptom severities and behavioral presentations. Individuals are positioned at different points along this spectrum based on the type and intensity of symptoms they exhibit, which can range from mild to severe.

Children with ASD commonly experience difficulties in both verbal and nonverbal communication, social interactions, and play-related activities. The primary cause of ASD remains unknown, though it is more prevalent in boys than girls. The disorder affects brain function in areas related to social interaction and communication skills, making it challenging for affected individuals to engage with others and the external world. In addition to these core symptoms, repetitive behaviors such as hand-flapping or jumping, resistance to change, and unusual sensory sensitivities (e.g., to sight, sound, touch, smell, or taste) are often observed.

A central feature of autism is impaired communication. Approximately 50% of children with ASD are unable to use spoken language as their primary means of communication. One common speech feature is the avoidance of personal pronouns like I, along with frequent echolalia, repetition of words and phrases spoken by others. Autism is widely considered one of the most complex and challenging psychiatric conditions of childhood (8). Verbal information is primarily processed and conveyed through words. The set of words an individual has at their disposal for communication is referred to as their vocabulary (9). Vocabulary is essential for communication in any language and constitutes a primary linguistic tool for conveying meaning. Vocabulary acquisition is a core component of language learning and is intricately linked to syntax, structure, and phonological development. One of the key factors influencing word recognition and processing is word frequency, defined as the number of times a word occurs within a given language. Based on frequency, words can be categorized as high-frequency or low-frequency. In various learning contexts, the processing priorities for high- and low-frequency words differ. It is not necessarily the case that high-frequency words are always easier to recall; the learning context often plays a critical role (10).

One common approach in studies of word frequency across different languages is measuring the number of words produced by a specific category or a particular letter at a given time (11). Studies have shown that age, gender, and education affect the performance of these tests (12).

Cues for information retrieval exist at various cognitive levels (perceptual and semantic). Perceptual cues (letters) refer to lower cognitive levels and are more related to the physical and visual properties of information, while semantic cues refer to higher cognitive levels and are associated with the conceptual and deeper characteristics of the information. The number of words produced based on a specific category is referred to as semantic verbal fluency. Semantic verbal fluency refers to a child's ability to produce words related to a concept or category. This ability can help an individual expand their memory, organize learned materials, enhance knowledge and information, and prevent both proactive and retroactive semantic interference (10). The number of words produced based on a specific letter is called phonemic verbal fluency. Phonemic verbal fluency involves the search and retrieval of words with a common initial letter. This function requires the ability to access phonological knowledge from the phonological memory store, and the individual must be able to extract words with the same initial letter from different semantic categories based on their phonological knowledge. Thus, this function requires the ability to shift from one category to a new classification (13).

In general, verbal fluency tests (VFT) are interpreted using only several spoken words, such as the number of words, the number of correct words, repetitions (persistent errors), and non-persistent errors. The results are just a characteristic, which is an important limitation of a neuropsychological test in both practice and clinical research. As a result, many researchers have considered additional features of VFT in their studies and adopted a qualitative approach to better understand the organization of semantic memory. One of these is clustering and switching scores (14). Converting spoken words into a graph (network) enables the analysis of their hidden features, which can help understand the dynamics and organization of cognitive processes (15).

2- METHODS

The present study is a post-hoc (causal-comparative) type. The participants were students from an autism school in Tabriz, aged 7 to 12 years, with an IQ range of 70 to 85 based on the Godinaff Intelligence Test. There was also a control group of students from regular elementary schools in Tabriz within the same age range. For sampling, 30 children from the autism spectrum were selected from an autism education center. Due to some children’s, lack of cooperation, 25 participants from the autism spectrum group were included in the study. For the control group, 30 students from regular elementary schools in Tabriz, ranging from first to sixth grade, were randomly selected using simple random sampling. General inclusion criteria for both groups (autistic and regular children) included: age between 7 to 12 years, parental consent for participation in educational interventions, enrollment in elementary school. Specific inclusion criteria for the test group (autistic children) included having ASD and an IQ of 70 to 85 according to the Godinaff Test. Exclusion criteria for both groups included: hearing and vision problems, concurrent use of similar psychological or educational programs, and a lack of willingness to cooperate from the teacher, parents, or child.

2-1. Instruments Used in This Study

2-1-1. Subtest of Word Creation with Letter Cues

This subtest includes three letters from the Persian alphabet (M, A, N), separately written in bold font on cards.

Each letter is shown to the participant and read aloud. The participant is asked to recall and loudly say as many words as they can that begin with the presented letter. The time allowed for word production for each letter is one minute, totaling three minutes for all three letters. The time used for each letter is recorded separately for each student. The Cronbach's alpha obtained for this test is 0.77.

2-1-2. Subtest of Word Creation with Category Cues

This subtest includes six categories (girls' names, boys' names, body parts, fruits, colors, and kitchen utensils), separately written in bold font on cards. The examiner shows each card and reads the category aloud, asking the child to name as many words as possible related to the presented category. The time allocated for each category is one minute, totaling six minutes for all six categories. The Cronbach's alpha obtained for this test is 0.76.

2-1-3. Speech Graphs Software

Speech Graphs is a computational tool successfully used in the differential diagnosis of psychosis through the structural analysis of nonsensical speech graphs. This approach provides quantitative, rapid, and cost-effective clinical measurements based on the free expression of words by the participant in a psychological test. The user of this software needs to understand how different methods of collecting speech data can impact such measurements. Speech pauses or interruptions in the patient's speech can directly affect the analysis of speech graphs. This software is developed using the Java programming language.

2-1-4. Graph

A graph is a mathematical model for a discrete set in which the members are connected in a specific way. The members of this set can represent multiple individuals, and their relationships might include actions such as shaking hands, being friends, or being relatives. The members can also be the connection points of electrical wires in a power grid, with their relationships being the wires linking two points. Members might be atoms in a molecule, with their relationships being chemical bonds, or they might represent various regions of the Earth, with bridges connecting them. Figure 1 illustrates examples of graph-based modeling applied to three distinct domains: brain region connectivity, the molecular structure of methane (CH_4), and social (friendship) networks. Graph theory has its roots in games and puzzles but is now a powerful tool for studying the structure of relationships between members of sets (16).

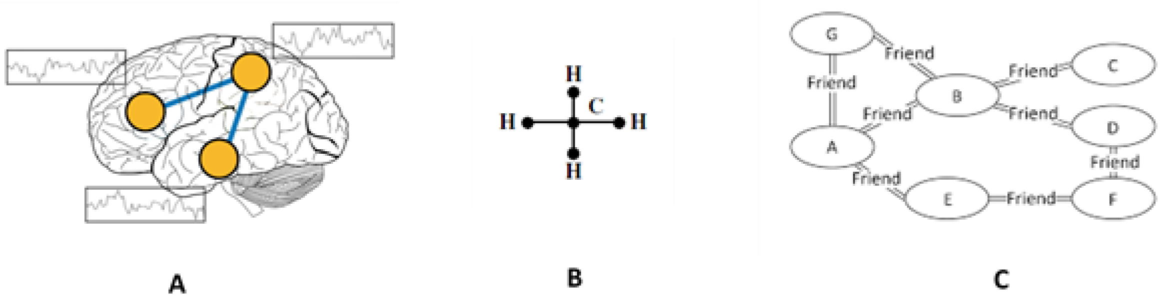

Figure-1: A) Graph-based modeling for brain region connectivity, B) hydrocarbon CH_4 structure, C) friendship relationships

2-1-5. Data Preparation

2-1-5-1. Graph Theory

In graph theory, a simple undirected graph G consists of two distinct sets: a non-empty set of elements called vertices (denoted by V(G)) and a set of edges (denoted by E(G)), which represent connections between pairs of vertices. Such a graph is formally defined as G = (V, E), where each edge is an element of a finite set of unordered pairs of vertices.

Graphs are generally classified into two main categories: undirected graphs and directed graphs, as described in Figure 2. In an undirected graph, if an edge e connects two vertices u and v, it is denoted as the unordered pair e ={u,v} or simply e = uv or e = vu. The vertices u and v are the endpoints of the edge e. Thus, the edge set E(G) in an undirected graph is a collection of unordered pairs of elements from the vertex set V(G), meaning that each edge connects two vertices without implying direction. In contrast, a directed graph (or digraph) consists of ordered pairs of vertices. Each directed edge (also called an arc) is represented by e = (u, v), or more concisely as e = uv, where u is the tail and v is the head of the arc. When uv ∈ E(G), we write u→v, indicating that there exists a directed edge from vertex u to vertex v.

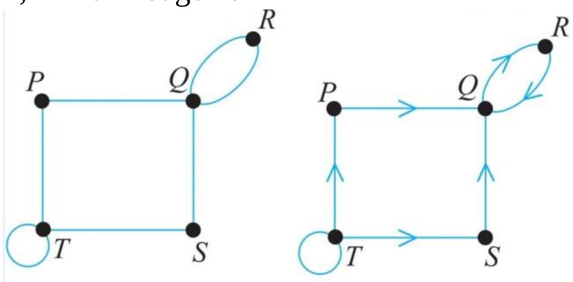

Figure-1: Undirected and Directed graphs.

2-1-5-2. Loop Definition

A loop is an edge whose both endpoints coincide, meaning it starts and ends at the same vertex.

2-1-5-3. Multiple Edges

Parallel edges are edges that connect the same pair of distinct vertices more than once.

2-1-5-4. Order Definition

The order of a graph is defined as the number of vertices it contains. It is denoted by p, where p =|V(G)|, and p is a natural number.

2-1-5-5. Size Definition

The number of edges in a graph is called its size and is denoted by q, that is, q =|E(G)|, where q is a non-negative integer.

2-1-5-6. Multiplicity Definition

The total number of edges connecting the same pair of vertices is referred to as the multiplicity and is denoted by RE.

2-1-5-7. Degree Definition

In a graph G, the degree of a vertex v, denoted by deg(v), is the number of edges incident to v. The maximum degree is denoted by Δ(G), and the minimum degree by δ(G). A loop contributes twice to the degree of a vertex.

2-1-5-8. Out-degree and In-degree Definition

In a directed graph, the number of edges that leave a vertex v is called the out-degree of v, denoted by od(v), and the number of edges that enter v is called the in-degree, denoted by id(v).

2-1-5-9. Simple and Multigraph Definition

A graph that contains neither loops nor multiple edges is called a simple graph, illustrated in Figure 3. A graph that allows loops and/or multiple edges between vertices is referred to as a multigraph.

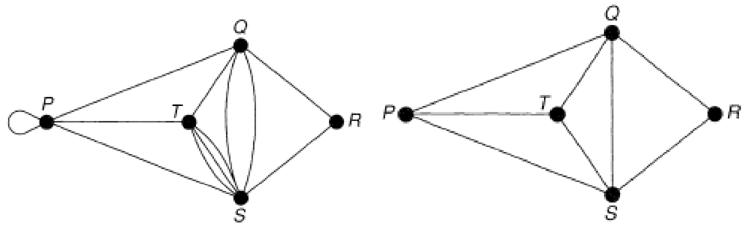

Figure-2: Simple and Multigraph Theory.

2-1-5-10. Average Total Degree Definition

The Average Total Degree of a graph is defined as the sum of the degrees of all vertices divided by the number of vertices. It is denoted by ATD.

2-1-5-11. Complete Graph Definition

A complete graph is a graph in which every pair of distinct vertices is connected by a unique edge.

2-1-5-12. Graph Density Definition

Graph density is a measure of how close a graph is to being complete. It is calculated as the ratio of the number of edges in the graph to the number of possible edges in a complete graph of the same order.

For an undirected simple graph: $Density = \frac{2q}{p(p-1)}$

For a directed graph without loops: $Density = \frac{q}{p(p-1)}$

For a directed graph with loops: $Density = \frac{q}{p^2}$

where q = |E(G)| is the number of edges and p = |V(G)| is the number of vertices.

2-1-5-13. Path Definition

In a graph G=(V,E), a path from vertex v_1 to vertex v_{n+1} ($n \in N$) is a sequence of distinct vertices $v_1, v_2, \ldots, v_n, v_{n+1}$ that $v_i, \ldots, v_{i+1} \in E$ for $i=1,\ldots,n$, $n_i=1,\ldots,n$. The length of the path is n, representing the number of edges in the sequence. A single vertex v_1 constitutes a path of length zero.

2-1-5-14. Cycle Definition

A cycle is a closed path that starts and ends at the same vertex without repeating any internal vertex. The length of a cycle is the number of edges it contains.

2-1-5-15. Connected Graph Definition

A graph is called connected if there exists a path between every pair of vertices. Otherwise, it is called disconnected. A disconnected graph can be decomposed into two or more components or subgraphs.

2-1-5-16. Subgraph Definition

Given a graph G=(V,E), a graph G′=(V′,E′) is a subgraph of G if V′⊆V and E′⊆E. A component of a graph is the largest connected subgraph, meaning the subgraph that contains the maximum number of edges among all connected subgraphs.

2-1-5-17. Strongly Connected Graph Definition

A directed graph G is called strongly connected if for every pair of vertices u and v, there exists a path from u to v and from v to u. The number of vertices in a strongly connected component is denoted by LSC.

2-1-5-18. Graph Diameter Definition

If G is a connected graph, the diameter of the graph, denoted by diam(G), is defined as the greatest distance (shortest path length) between any two vertices in the graph.

2-1-5-19. Adjacency and Incidence Matrix Definition

Let G=(V, E) be a graph with vertex set $V=\{v_1,v_2,\ldots,v_p\}$ and edge set $E=\{e_1,e_2,\ldots,e_q\}$. The adjacency matrix of G, denoted by $A(G)=[a_{ij}]$, is a square matrix of order p×p in which each entry a_{ij} represents the number of edges connecting vertex v_i to vertex v_j. The incidence matrix of G, denoted by $M(G)=[m_{ij}]$, is a p×q matrix in which each element m_{ij} indicates the number of times (0, 1, or 2) that vertex v_i is incident to edge e_j. Both the adjacency and incidence matrices provide alternative representations of a graph, as outlined below. In general, the adjacency matrix is significantly smaller in size than the incidence matrix, and as a result, it is more commonly used in computer-based graph storage and processing.

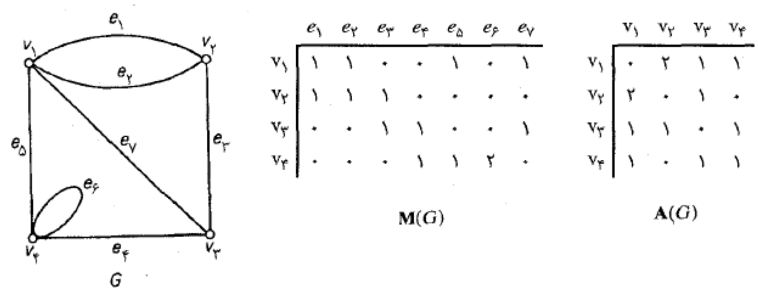

Figure-3: Adjacency and Incidence Matrix of G.

2-1-5-20. One-Vertex Cycles Definition

The number of one-vertex cycles, denoted by L_1, is equal to the sum of all loops (self-edges) connected to a single vertex plus the vertex itself. It can be computed using the trace (diagonal sum) of the adjacency matrix A(G) of the graph.

2-1-5-21. Two-Vertex Cycles Definition

The number of two-vertex cycles, denoted by L_2, represents all cycles that include exactly two vertices. It is calculated as the trace of the square of the adjacency matrix A^2(G) divided by 2, as shown below.

$$L_2 = \frac{trace(A^2(G))}{2} \qquad (1)$$

2-1-5-22. Three-Vertex Cycles Definition

The number of three-vertex cycles (i.e., triangles), denoted by L_3, includes all cycles formed by exactly three distinct vertices. It is calculated as the trace of the cube of the adjacency matrix A^3(G) divided by 3, as shown below.

$$L_3 = \frac{trace(A^3(G))}{3} \qquad (2)$$

2-1-5-23. Average Shortest Path Definition

The Average Shortest Path (ASP) in a network is defined as the average length of the shortest paths between all pairs of vertices in the graph. It provides an overall measure of the graph's navigability and communication efficiency.

2-1-5-24. Clustering Coefficient Definition

The clustering coefficient is a measure of the degree to which nodes in a graph tend to cluster together. It is generally divided into two types: global clustering coefficient and local clustering coefficient.

2-1-5-24-1. Global Clustering Coefficient

This coefficient is based on the number of connected triplets and the number of closed triplets (i.e., triangles) in the graph. A triplet consists of three nodes connected by either two (open triplet) or three (closed triplet/triangle) edges. In a triangle, each of the three nodes is the center of a triplet. The global clustering coefficient is defined as:

$$C = \frac{No.of\ \text{triangles} \times 3}{No.of\ connected\ \text{triplets of vertices}} = \frac{No.of\ \text{closed triplets}}{No.of\ connected\ \text{triplets}} \quad (3)$$

2-1-5-24-2. Local Clustering Coefficient

The local clustering coefficient of a vertex quantifies how close its neighbors are to forming a complete subgraph (i.e., a clique). It measures the likelihood that two neighbors of a node are also neighbors of each other. This provides a sense of the local cohesiveness or cliquishness of the graph around that vertex.

Let G (V, E) be a directed graph, where the edge $e_{ij} \in E$ connects vertex v_i to vertex v_j. The neighborhood of a vertex v_i, denoted by N_i, is defined as the set of all vertices that are directly connected to v_i either by incoming or outgoing edges:

$$N_i = \{v_j : e_{ij} \in E \ \vee \ e_{ji} \in E\} \quad (4)$$

The number of neighbors of v_i is denoted by $k_i = |N_i|$.

The local clustering coefficient C_i of vertex v_i is defined as the ratio of the number of existing directed edges among the nodes in N_i to the total number of possible directed edges among them. In a directed graph, where e_{ij} and e_{ji} are considered distinct, the maximum number of possible directed edges among k_i neighbors is $k_i(k_i-1)$. Thus, the local clustering coefficient C_i is given by:

$$C_i = \frac{|\{e_{jk} : v_j, v_k \in N_i, e_{jk} \in E\}|}{k_i(k_i-1)} \quad (5)$$

This coefficient reflects the tendency of a node's neighbors to be connected in a directed manner, and it ranges from 0 (no interconnection among neighbors) to 1 (fully connected neighborhood in the directed sense). In undirected graphs, edges are symmetric, meaning that $e_{ij} = e_{ji}$. If a vertex v_i has k_i neighbors, then the maximum number of possible edges that can exist among the neighbors in the neighborhood N_i is given by:

$$\frac{ki(ki-1)}{2} \quad (6)$$

The local clustering coefficient C_i for vertex v_i in an undirected graph is defined as the ratio of the number of actual edges among the neighbors of v_i to the total number of possible edges among them. This can be expressed as:

$$C_i = \frac{2|\{e_{jk} : v_j, v_k \in N_i, e_{jk} \in E\}|}{k_i(k_i-1)} \quad (7)$$

This coefficient measures how close the neighborhood of a node is to forming a complete subgraph (clique). A local clustering coefficient of 1 indicates that every neighbor of v_i is connected to every other neighbor (i.e., a complete subgraph), while a coefficient of 0 indicates no connections among neighbors.

Let $\lambda_G(v)$ denote the number of triangles in an undirected graph G that include the vertex v. Each triangle is a 3-vertex, 3-edge subgraph in which one of the vertices is v. Let $\tau_G(v)$ denote the number of triplets centered at v; that is, the number of (not necessarily induced) subgraphs consisting of three vertices and two edges where v is the common endpoint of both edges (i.e., the center of the triplet). Then, the local clustering coefficient C_i of vertex v can be defined as:

$$C_i = \frac{\lambda_G(v)}{\tau_G(v)} \qquad (8)$$

This definition is equivalent to the previous formula (Equation 6-7), because:

$$\tau_G(v) = \binom{k_i}{2} = \frac{1}{2}k_i(k_i - 1) \qquad (9)$$

where k_i is the degree of vertex v_i, i.e., the number of its immediate neighbors.

As an alternative to the global clustering coefficient based on triangle counts, the average local clustering coefficient is often used to quantify the overall clustering tendency of the network. It is computed as the average of the local clustering coefficients across all n vertices:

$$\bar{C} = \frac{1}{n}\sum_{i=1}^{n} C_i \qquad (10)$$

This metric provides a scalar measure of how tightly the graph's nodes tend to cluster.

To construct speech feature graphs using the SpeechGraphs software, the spoken words are considered as nodes, and the temporal connections between successive words are considered as edges (Lais Bertola et al., 2014). After entering the data from phonemic and semantic verbal fluency tasks into the software, the following network indices are automatically calculated: Word Count (WC), Number of Nodes, Number of Edges, Repeated Edges (RE), Parallel Edges (PE), Loops of Size 1 (L1), Loops of Size 2 (L2), Loops of Size 3 (L3), Largest Connected Component (LCC), Largest Strongly Connected Component (LSC), Average Total Degree (ATD), Density, Diameter, Average Shortest Path (ASP), and Clustering Coefficient (CC). As a detailed example, in a semantic verbal fluency task with the category birds, a participant was asked to name as many related items as possible. The responses were saved in a .txt file, typed sequentially with a space separating each word. The participant's response was: Crow, pigeon, duck, eagle, falcon, crow, dove, canary, duck, pigeon, parrot, pelican, penguin, parrot, owl, owl.

The resulting directed graph is shown in Figure 5, and the corresponding network measures calculated by SpeechGraphs are shown in Table 1.

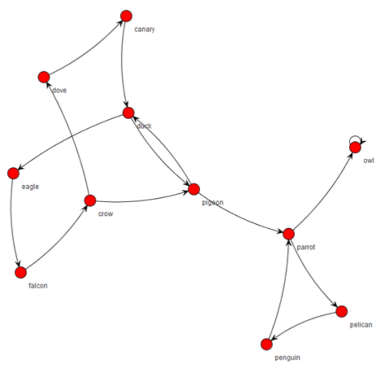

Figure-5: Speech directed graph from the SVF task with the category 'birds'.

Table-1 : Topological features of the speech graph from the SVF task (bird category).

Metric	Value	Metric	Value
WC	16	Nodes	11
Edges	15	RE	0
PE	1	L1	1
L2	1	L3	1
LCC	11	LSC	7
ATD	2.72	Density	0.24
Diameter	4	ASP	2.42
CC	0.20		

Table-2 : Descriptive Findings of the Phonemic Verbal Fluency Test and Its Speech Graph Features.

Dependent Variable	Group	N	Mean	SD	Min	Max
Phonemic Verbal Fluency (Letter)	Autism	25	6.88	3.53	1	15
	Control	30	22.00	6.79	8	44
Number of Nodes	Autism	25	6.48	3.32	1	15
	Control	30	21.57	6.68	8	42
Number of Edges	Autism	25	5.80	3.40	0	14
	Control	30	20.80	6.67	8	42
Repeated Edges	Autism	25	0.00	0.00	0	0
	Control	30	0.00	0.00	0	0
Parallel Edges	Autism	25	0.04	0.20	0	1
	Control	30	0.00	0.00	0	0
Loops of Size 1	Autism	25	0.20	0.50	0	2
	Control	30	0.13	0.35	0	1
Loops of Size 2	Autism	25	0.04	0.20	0	1
	Control	30	0.00	0.00	0	0
Loops of Size 3	Autism	25	0.04	0.20	0	0
	Control	30	0.00	0.00	0	0
Largest Connected Component (LCC)	Autism	25	6.08	3.35	1	15
	Control	30	21.57	6.67	8	42
Largest Strongly Connected Component (LSC)	Autism	25	1.12	0.44	1	3
	Control	30	1.43	1.45	1	8
Average Total Degree	Autism	25	1.58	0.63	0	2.5
	Control	30	1.93	0.05	1.86	2
Density	Autism	25	0.28	0.15	0	0.50
	Control	30	0.11	0.05	0.05	0.29
Diameter	Autism	25	5.36	3.28	0	14
	Control	30	20.23	6.29	5	38
Average Shortest Path	Autism	25	2.38	1.24	0	5.33
	Control	30	7.38	2.11	2.32	13.27
Clustering Coefficient	Autism	25	0.01	0.05	0	0.24
	Control	30	0.00	0.00	0	0

3- RESULTS

In the present study, participants were divided into two groups: Autism and Control (typically developing). Among the individuals in the autism group, there were 5 girls and 20 boys, while the control group included 15 girls and 15 boys. The age distribution of the participants was also examined. In the autism group, the distribution was as follows: one participant aged 7–8 years, four participants aged 8–9 years, five participants aged 9–10 years, four participants aged 10–11 years, seven participants aged 11–12 years, and four participants aged 12–13 years. In the control group, five participants were randomly selected from regular schools in each of the aforementioned age ranges.

Two subtests were administered to both groups: A letter-cued word fluency task, which included three Persian letters (M, N, A), and a category-cued word fluency task, which included six categories (girl names, boy names, body parts, fruits, colors, and kitchen utensils). Following the verbal fluency tasks, speech graphs and network metrics were extracted for each participant using the SpeechGraphs software. The results are presented in Tables 2 and 3.

Table-3: Descriptive findings of the semantic verbal fluency task and its speech feature graph characteristics

Dependent Variable	Group	NO.	Mean	STD	Min	Max
Semantic Verbal Fluency (Category)	Autism	25	32.68	7.45	14	46
	Healthy	30	50.90	10.61	33	74
Number of Nodes	Autism	25	30.16	7.30	14	41
	Healthy	30	50.53	10.61	34	75
Number of Edges	Autism	25	30.16	7.64	13	43
	Healthy	30	49.93	10.80	33	74
Repeated Edges	Autism	25	0.12	0.44	0	2
	Healthy	30	0	0	0	0
Parallel Edges	Autism	25	0.20	0.50	0	2
	Healthy	30	0.03	0.18	0	1
Loops of Size 1	Autism	25	0.08	0.40	0	2
	Healthy	30	0.03	0.18	0	1
Loops of Size 2	Autism	25	0.12	0.33	0	1
	Healthy	30	0.03	0.18	0	1
Loops of Size 3	Autism	25	0.24	0.44	0	1
	Healthy	30	0.10	0.40	0	2
Largest Connected Component	Autism	25	30.20	7.31	14	41
	Healthy	30	50.53	10.61	34	75
Largest Strongly Connected Component	Autism	25	3.08	2.41	1	8
	Healthy	30	1.80	1.63	1	6
Average Total Degree of Nodes	Autism	25	1.99	0.82	1.86	2.18
	Healthy	30	1.97	0.03	1.94	2.05
Density	Autism	25	0.07	0.02	0.05	0.14
	Healthy	30	0.04	0.01	0.03	0.06
Diameter	Autism	25	27.36	6.52	13	39
	Healthy	30	48.70	10.39	31	74
Average Shortest Path	Autism	25	9.74	2.24	5	13.67
	Healthy	30	16.93	3.53	11.45	25.33
Clustering Coefficient	Autism	25	0.02	0.03	0	0.10
	Healthy	30	0.003	0.012	0	0.06

In this study, an independent samples t-test will be utilized to examine the differences in means between the group of children with ASD and the control (healthy) group. Before conducting this parametric test, the assumptions of the t-test (interval scale, normality of distribution, homogeneity of variances, and independence of observations) will be verified. If any of these assumptions are violated, a non-parametric alternative, specifically the Mann-Whitney U test, will be used to analyze the data. This approach ensures that the analysis is robust and appropriate for the given data, taking into consideration the underlying assumptions of the tests. Table 4 indicates that the assumption of normality for the dependent variables in the phonemic verbal fluency test (letters) has not been met in the sample under study. This is evident because the calculated Z-values are statistically significant at $p<0.05$, suggesting that the data distribution is not normal.

Moreover, Table 5 shows that the significance level (Sig) for the dependent variables is less than 0.05, indicating that the variances between the two groups are not equal. Given that the data are not normally distributed and the variances of the two groups are not homogeneous, the non-parametric Mann-Whitney U test will be used to examine the speech graph features of the phonemic verbal fluency test

Table-4: The results of the Kolmogorov-Smirnov test for checking the normality of the distribution of verbal fluency scores (phonemic).

Dependent Variable	Z Statistic	Significance Level (Sig)
Phonemic Verbal Fluency (Letters)	0.143	0.007
Number of Nodes	0.149	0.004
Number of Edges	0.141	0.008
Repeated Edges	-	-
Parallel Edges	0.535	0.000
Single-Cycle Loops	0.506	0.000
Double-Cycle Loops	0.535	0.000
Triple-Cycle Loops	0.535	0.000
Largest Connected Component	0.157	0.002
Strongly Connected Component	0.512	0.000
Average Node Degrees	0.307	0.000
Density	0.190	0.000
Diameter	0.159	0.001
Average Shortest Path	0.148	0.004
Clustering Coefficient	0.535	0.000

Table-5: The Levene's Test for Homogeneity of Variance of the Error Scores for Phonemic Verbal Fluency.

Dependent Variable	F Statistic	Sig.
Phonemic Verbal Fluency (Letters)	4.376	0.041
Number of Nodes	6.987	0.011
Number of Edges	6.588	0.013
Repeated Edges	-	-
Parallel Edges	5.246	0.026
Single-Cycle Loops	1.577	0.215
Two-Cycle Loops	5.246	0.026
Three-Cycle Loops	5.246	0.026
Largest Connected Component	7.032	0.011
Largest Strongly Connected Component	4.856	0.032
Mean Sum of Node Degrees	16.701	0.0002
Density	17.366	0.0001
Diameter	6.160	0.016
Mean Shortest Path	4.794	0.033
Clustering Coefficient	5.246	0.026

Table 6 shows that there are significant differences between children with ASD and typically developing children in phonemic verbal fluency (letters) and its speech graph features, including nodes, edges, largest connected component, largest strongly connected component, mean sum of node degrees, density, diameter, and mean shortest path, with a significance level of $p<0.05$. However, no significant differences were found between the two groups for other speech graph features of phonemic verbal fluency. To analyze the speech graph features of the semantic verbal fluency test (categories), the assumptions of the independent t-test need to be examined.

Table 7 indicate that the assumption of normality for the dependent variables in the semantic verbal fluency test has been met for certain variables: semantic verbal fluency, number of nodes, number of edges, largest connected component, diameter, and mean shortest path, as the calculated Z values are not significant at the $p<0.05$ level. For the other dependent variables, the normality assumption has not been met.

Table-6 : The results of the Mann-Whitney U test for phonemic verbal fluency.

Dependent Variable	Z-Statistic	Sig
Phonemic Verbal Fluency (Letters)	-6.097	0.000
Number of Nodes	-6.153	0.000
Number of Edges	-6.172	0.000
Repeated Edges	0.000	1.000
Parallel Edges	-1.095	0.273
Single-Node Cycles	-0.332	0.740
Two-Node Cycles	-1.095	0.273
Three-Node Cycles	-1.095	0.273
Largest Connected Component	-6.171	0.000
Largest Strongly Connected Component	-0.356	0.722
Mean Sum of Node Degrees	-3.566	0.000
Density	-4.576	0.000
Diameter	-6.047	0.000
Mean Shortest Path	-5.973	0.000
Clustering Coefficient	-1.095	0.273

Table-7 : The results of the Kolmogorov-Smirnov test for assessing the normality of the distribution of semantic verbal fluency scores.

Dependent Variable	Z Statistic	Sig
Semantic Verbal Fluency	0.089	0.200
Number of Nodes	0.072	0.200
Number of Edges	0.068	0.200
Repeated Edges	0.536	0.000
Parallel Edges	0.525	0.000
Single-Cycle Edges	0.536	0.000
Double-Cycle Edges	0.537	0.000
Triple-Cycle Edges	0.506	0.000
Largest Connected Component	0.072	0.200
Strongly Connected Component	0.363	0.000
Mean Degree Sum of Nodes	0.186	0.000
Density	0.205	0.000
Diameter	0.096	0.200
Mean Shortest Path	0.083	0.200
Clustering Coefficient	0.504	0.000

The contents of Table 8 show that the significance level (Sig) for the dependent variables Repeated Edges, Parallel Edges, Double-Cycle Edges, Triple-Cycle Edges, Strongly Connected Component, Mean Degree Sum of Nodes, Density, Diameter, and Clustering Coefficient is less than 0.05, indicating that the variances between the two groups for these variables are not equal. For the other dependent variables, Semantic Verbal Fluency (Category), Number of Words, Number of Nodes, Single-Cycle Edges, Largest Connected Component, and Mean Shortest Path, the variances of the groups of children with ASD and typically developing children are equal in the semantic verbal fluency and graph-theoretical features tests. Based on the assumptions of the parametric independent t-test, for the dependent variables Semantic Verbal Fluency, Number of Nodes, Number of Edges, Largest Connected Component, and Mean Shortest Path, we will use the t-test, while for the other dependent variables, we will use the non-parametric Mann-Whitney U test.

Furthermore, the calculated t-statistic for the dependent variables in Table 9, with 53 degrees of freedom, is greater than the critical value from the table (for 55 < df < 60, we have 2.004 < t < 2.000). Therefore, there is a significant difference between the verbal fluency (semantic) and speech graph features, including the number of nodes, number of edges, largest connected component, and mean shortest path, between children with ASD and typically developing children.

Table-8: The Levene's Test for Homogeneity of Variance of Verbal Fluency.

Dependent Variable	Z Statistic	Sig
Verbal Fluency (Semantic)	1.560	0.217
Number of Nodes	1.436	0.236
Number of Edges	1.006	0.320
Repeated Edges	10.299	0.002
Parallel Edges	13.259	0.001
Univariate Cycles	1.404	0.241
Bivariate Cycles	6.576	0.013
Trivariate Cycles	4.692	0.035
Largest Connected Component	1.382	0.245
Strongly Connected Largest Component	6.609	0.013
Mean Total Degree of Nodes	21.335	0.000
Density	12.979	0.001
Diameter	4.190	0.046
Mean Shortest Path	3.513	0.066
Clustering Coefficient	18.953	0.000

Table-9: The Independent t-test Results for Verbal Fluency (Semantic).

Dependent Variable	F-Statistic	Sig	t-Statistic	Degrees of Freedom (df)	Two-Tailed Significance Level
Verbal Fluency (Semantic)	1.560	0.217	-7.222	53	0.000
Number of Nodes	1.436	0.236	-8.126	53	0.000
Number of Edges	1.006	0.320	-7.686	53	0.000
Largest Connected Component	1.382	0.245	-8.106	53	0.000
Mean Shortest Path	3.513	0.066	-8.808	53	0.000

Based on the results from the non-parametric U Mann-Whitney test, Table 10 shows that in the speech graph features of the semantic verbal fluency test, including the largest strongly connected component, density, and diameter, there is a significant difference ($p < 0.05$) between children with ASD and typically developing children. However, there is no significant difference between the two groups in the speech graph features of semantic verbal fluency, including recurrent edges, parallel edges, single-node cycles, two-node cycles, three-node cycles, average degree sum of nodes, and dryness coefficient.

Figures 6 and 7 illustrate representative examples of speech graphs derived from the semantic and phonemic verbal fluency tasks, respectively. Figure 6 shows the speech graph of a participant from the autism group, highlighting lower graph connectivity and a more constrained structure. In contrast, Figure 7 presents the speech graph of a participant from the neurotypical group, characterized by a more interconnected and expansive network. These graphical representations visually reflect the quantitative differences reported in Tables 9 and 10, emphasizing reduced fluency and altered speech structure in individuals with autism.

Table-10: The Mann-Whitney U Test Results for Semantic Verbal Fluency.

Dependent Variable	Z Statistic	Sig
Recurrent Edges	-1.563	0.118
Parallel Edges	-1.628	0.104
Single-node Cycles	-0.156	0.876
Two-node Cycles	-1.221	0.222
Three-node Cycles	-1.714	0.087
Largest Strongly Connected Component	-2.420	0.016
Average Degree Sum of Nodes	-0.316	0.752
Density	-5.802	0.000
Diameter	-5.980	0.000
Dryness Coefficient	-1.861	0.063

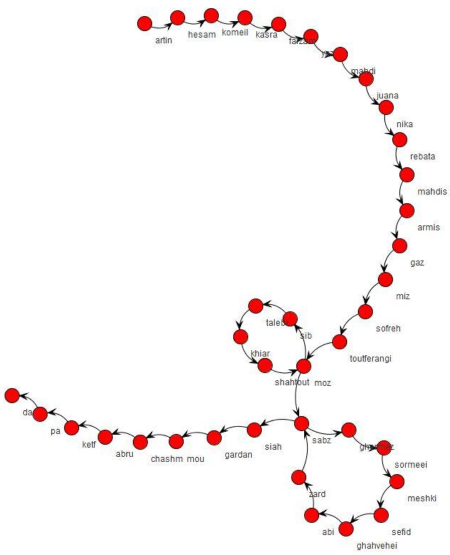

Figure-4 : An example of semantic verbal fluency speech graphs – Autism group.

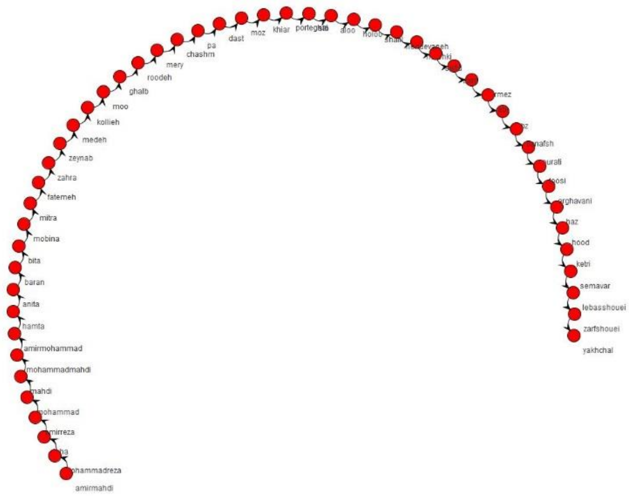

Figure-5: An example of phonemic verbal fluency speech graphs – Neurotypical group.

4- DISCUSSION

In verbal fluency tasks, each participant is assigned both a phonemic fluency score and a semantic fluency score. Researchers then seek to identify significant differences and meaningful relationships between the experimental groups. In both national and international studies, statistical analysis methods have been widely employed to investigate verbal fluency in children, particularly those diagnosed with ASD, yielding valuable findings. However, given that cognitive science is an interdisciplinary field, relying solely on statistical methods may not fully address the complex needs of researchers in this domain. On the other hand, the transformative impact of mathematics and computer science on a wide range of disciplines is undeniable. One area that bridges these two fields is graph theory. Therefore, we aimed to apply graph theory and its cognitive science applications, particularly within cognitive psychology and cognitive linguistics. This is the first study to employ graph theory to analyze VFT in children with ASD. Inspired by previous studies investigating verbal fluency in individuals with schizophrenia, bipolar disorder, mania, and related conditions, we adopted a graph-based analytical approach to examine various general graph features, including: number of nodes, number of edges, repeated edges, parallel edges, self-loops, two-node cycles, three-node cycles, largest connected component, largest strongly connected component, average node degree, graph density, graph diameter, average shortest path length, and clustering coefficient.

The ASD group produced fewer words in the phonemic verbal fluency task compared to the typically developing (TD) group. Correspondingly, the phonemic verbal fluency graphs of children with ASD demonstrated fewer nodes and edges, as well as noticeable differences in global graph features relative to the control group. Specifically, the ASD group exhibited a smaller largest connected component, a smaller largest strongly connected component, shorter average shortest path length, higher density, smaller diameter, and lower average node degree. In the semantic verbal fluency task, children with ASD also generated fewer words compared to the TD group. Their semantic VFT graphs revealed a reduced number of nodes and edges, along with the following differences: a smaller largest connected component, a larger largest strongly connected component, shorter average shortest path length, higher density, and smaller graph diameter.

Furthermore, findings from this study suggest that word production based on phonemic cues (i.e., letters) is more challenging for participants in both groups compared to semantic category-based word generation. Gilman and Huffman argue that categorization and switching are two components of verbal fluency that are not directly tied to linguistic knowledge. Semantic fluency requires categorization, the ability to generate words that belong to the same cluster (category), whereas phonemic fluency involves switching between categories (initial letters). Based on this perspective, phonemic verbal fluency appears to be more cognitively demanding than semantic fluency, as it relies more heavily on executive functions and frontal lobe activity (17).

The data suggest that the reduced word production in phonemic or semantic fluency may reflect increased time spent by individuals navigating through related nodes in a semantic speech graph (network), where the generated words are expected to be closely related to a target phonemic or semantic cue. Additionally, patients may produce fewer words due to spending more time inhibiting incorrect responses or monitoring problematic ones.

Changes in global graph features indicate that patients produce non-linear speech graphs, characterized by shorter paths from the first to the last word, and by additional, potentially irrelevant, connections between generated words. Graph-based analysis of verbal fluency allowed us to identify differences, such as higher density in ASD group graphs for both phonemic and semantic tasks, that are not captured through conventional scoring metrics.

Our results align with findings from other studies employing alternative analytical methods, such as multidimensional scaling and clustering techniques, on semantic networks produced by children with ASD. These studies also point to disorganized semantic structure and reduced vocabulary size in ASD populations.

Bertola et al. (2014) demonstrated that Speech Graph Analysis (SGA) can distinguish between patients with mild cognitive impairment (MCI), Alzheimer's disease, and healthy control groups (15). Their findings revealed that as cognitive impairment worsens, semantic verbal fluency graphs become denser, with reduced diameter, ASP, number of nodes, and number of edges. Furthermore, graph diameter and ASP values were among the most prominent distinguishing features across healthy aging, MCI, and Alzheimer’s groups, suggesting their strong association with general cognitive deficits.

Unlike standard measures, SGA was able to distinguish between individuals with bipolar disorder (BD) and healthy controls (HC). BD patients showed significant differences in the diameter and ASP of speech graphs derived from semantic VFT. Consequently, they produced less linear, weaker networks with substantially smaller diameters. Although no significant difference in performance between SZ and BD groups was observed, fewer SGA features could differentiate BD from HC compared to SZ. This may be related to the observation that, in that study, BD patients did not differ from HCs in standard verbal fluency metrics, unlike SZ patients. Nevertheless, SGA enabled the differentiation between these groups, suggesting that in the case of BD patients, speech graph analysis may be more sensitive than traditional measures based solely on productivity and error scores. Working memory, executive functioning, and processing speed scores are associated with both semantic and phonemic VFT performance in BD patients. Zhang et al. (2022) analyzed the topology of speech graphs generated in a semantic verbal fluency task (18). The speech graphs of Parkinson’s disease patients were smaller and denser than those of healthy controls, yet larger and more dispersed than those of Alzheimer’s disease patients. Moreover, Parkinson’s patients who produced smaller and denser graphs exhibited more severe non-motor symptoms.

5- CONCLUSION

This study demonstrated that children with ASD exhibit distinct patterns of speech organization, as shown by speech graph analysis of verbal fluency tasks. In comparison to typically developing peers, children with ASD produced fewer words and constructed speech graphs with fewer nodes and edges, smaller connected components, shorter average paths, and greater density.

These findings suggest that graph theory offers a powerful computational framework for understanding language impairments in neurodevelopmental disorders. By going beyond traditional scoring systems, speech graph metrics provide detailed insights into the structure and dynamics of spoken language in ASD. Such approaches can from the basis for developing innovative, computer-assisted tools for early detection, diagnosis, and rehabilitation of language deficits in children with ASD.

6- LIMITATIONS

This study has several limitations that should be acknowledged. First, the Kormi-Nouri VFT employed in this research was administered in an interview-based format. Given that children with ASD are characterized by significant impairments in social communication and interaction, the use of an interview-based assessment poses a specific methodological constraint for this population.

Second, the study sample consisted of children aged 7 to 12 years with ASD and typically developing peers. This age-restricted and demographically homogeneous sample limits the generalizability of the findings to the broader population, which is more heterogeneous in terms of demographic and clinical characteristics. Although the original design intended to recruit 30 students with ASD from a specialized autism school, only 25 participants were ultimately included due to factors such as cleft palate, social withdrawal, communication difficulties that precluded test administration, and exceeding the age limit.

It is recommended that the topic of graph theory and its applications be more extensively integrated into the curriculum of cognitive modeling courses at the Master's level in cognitive psychology, as well as in relevant doctoral-level courses in cognitive science. The utility of graph theory is not limited to verbal fluency tasks alone but also holds considerable promise in the analysis of other cognitive functions such as memory.

Patients with psychiatric disorders typically obtain lower scores on both phonemic and semantic verbal fluency tasks compared to healthy controls. The schematic characteristics and computational indices derived from speech graph analysis may offer novel perspectives for researchers and clinicians. In cases where patients’ speech graph metrics deviate significantly from normative benchmarks, targeted intervention and training programs can be designed to enhance specific impaired indices.

As a foundational tool in computer science and engineering, graph theory holds substantial potential for interdisciplinary applications. Given the direct influence and proven efficacy of computer-based cognitive rehabilitation methods, integrating graph-based analysis of verbal fluency into the development of digital language rehabilitation tools for clinical populations appears both feasible and promising. Achieving this goal requires cross-disciplinary collaboration and innovation.

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8-CONFICT OF INTEREST

The authors declare that there is no conflict of interest related to this research.

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