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Speech graph analysis in obsessive-compulsive disorder: The relevance of dream reports

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ABSTRACT

Obsessive-compulsive disorder (OCD) is a distressing disorder characterized by the presence of intrusive thoughts, images or urges (obsessions) and/or behavioral efforts to reduce the anxiety (compulsions). OCD lifetime prevalence varies between 1% and 3% in the general population and there are no reliable markers that support the diagnosis. In order to fill this gap, Computational Psychiatry employs multiple types of quantitative analyses to improve the understanding, diagnosis, prediction, and treatment of mental illnesses including OCD. One of these computational tools is speech graphs analysis. A graph represents a network of nodes connected by edges: in non-semantic speech graphs, nodes correspond to words and edges correspond to the directed link between consecutive words. Using non-semantic speech graphs, we compared free speech samples from OCD patients and healthy controls (HC), to test whether speech graphs analysis can grasp structural differences in speech between these groups. To this end, 39 OCD patients and 37 HC were interviewed and recorded during six types of speech reports: yesterday, dream, old memory, positive image, negative image and neutral image. Also, the Obsessive-Compulsive Inventory-Revised (OCI-R) and the Yale Brown Obsessive-Compulsive Scale (Y-BOCS) were used to assess symptom severity. The graph-theoretical structural analysis of dream reports showed that OCD patients have significantly smaller lexical diversity, lower speech connectedness and a higher recurrence of words in comparison with HC. The other five report types failed to show differences between the groups, adding to the notion that dream reports are especially informative of speech structure in different psychiatric states. Further investigation is necessary to completely assess the potential of this tool in OCD.

1. Introduction

Obsessive-Compulsive Disorder (OCD) is a debilitating psychiatric condition characterized by unwanted thoughts, images, or urges (obsessions) that intrude forcibly into the mind. The patient attempts to exclude the obsessional urge, which is perceived to be inappropriate and nonsensical. Furthermore, the illness may comprise repetitive behaviors or mental acts (compulsions) engaged to reduce the anxiety provoked by obsessions (Harrison et al., 2017). According to the criteria established by the Diagnostic and Statistical Manual of Mental Disorders (DSM-5), the diagnosis of OCD requires the presence of either obsessions or compulsions, or both. Additionally, symptoms must consume more than 1 h daily and must cause clinically significant distress. The OCD lifetime prevalence in the general population varies between 1% and 3% (Hirschtritt et al., 2017). According to the National Comorbidity Survey Replication (Ruscio et al., 2010), obsessive-compulsive symptomatology that did not meet the full criteria for DSM-4 was reported by 25% of those surveyed, which raises the doubt about the efficacy of OCD diagnosis. As prevalence is thought to be underestimated, it may be useful to find complementary diagnosis approaches.

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Despite the successive DSM editions and the advances in neuroscience, concrete improvement for patients suffering from mental illness has been slow (Hirschtritt et al., 2017; Ruscio et al., 2010). In fact, methodological objectivity for differential diagnosis remains difficult to achieve, and there are no markers able to reliably differentiate psychiatric health from illness at the level of the individual (Insel, 2010; Bedi et al., 2015).

Computational Psychiatry is a multidisciplinary field that incorporates methods from computation, psychiatry, psychology, neuroscience, ethology, economics and machine learning. Its objective is to quantify neuropsychological features and build mathematical models of neural or cognitive phenomena relevant to psychiatric diseases, facilitating the development of clinical treatment and decision tools (Huys et al., 2016; Wang and Krystal, 2014; Seifritz and Hasler, 2017). For instance, Computational Psychiatry attempts to provide quantitative phenotyping for relevant psychiatric symptoms (Huys et al., 2016; Wang and Krystal, 2014; Mota et al., 2016, 2017). A great amount of published work on this field concerns neuroscience and neuronal networks (Huys et al., 2016; Wang and Krystal, 2014; Bullmore and Sporns, 2009). However, herein we will focus on another specific computational tool: the assessment of verbal reports by graph analysis, which provides a precise and automated quantification of speech features (Mota et al., 2017).

In 2005, Bales et al. showed that networks generated from natural language had topological properties common to other natural phenomena (Bales and Johnson, 2006). Therefore, large network analysis could be applied to obtain quantitative measures of speech (Mota et al., 2012). It is possible to transform a speech report into a non-semantic speech graph and to characterize it structurally (Mota et al., 2012, 2015). In this context, a graph represents a network with nodes connected by edges, in which nodes correspond to words and edges correspond to the link between consecutive words, regardless of the meaning of the words (Bales and Johnson, 2006; Mota et al., 2012; Cancho and Solé, 2001; Butts, 1979). A non-semantic speech graph is a directed network, characterized by having each node connected to a following node by a directed edge, indicated by an arrow. A non-semantic speech graph also corresponds to a special kind of network called multigraph, in which self-loops (edges connecting a node to itself) and multiple edges (two nodes connected by more than one edge) may occur (Mota et al., 2012; Butts, 1979; Bollobás, 1998).

The first publications using speech and graph theory studied aspects of non-pathological language (Cancho and Solé, 2001; Sigman and Cecchi, 2002). Since then, numerous studies were developed in the last decade to evaluate the utility of speech graphs in psychiatric diagnosis, mainly in psychosis, by assessing either spoken or written discourse (Mota et al., 2012, 2015, 2017; Palaniyappan et al., 2019). These studies consistently demonstrated that, in patients with psychosis, non-semantic speech graphs analysis is a fast and low-cost complement to the diagnosis of schizophrenia, effectively functioning as a "laboratory test" for psychiatric disorders (Mota et al., 2012, 2015, 2017, 2018).

The application of non-semantic speech graphs analysis to psychiatric illnesses other than psychosis remains as a current goal. Thus, in the present work, we aim to evaluate whether OCD patients present differential structural speech features when compared to healthy controls (HC). For purpose of simplicity, the term "speech graph" will henceforth be equivalent to "non-semantic speech graph", since this work focuses on speech structure and not on semantics.

2. Material and methods

2.1. Participants

Thirty-nine OCD patients and thirty-seven matched controls participated in this study. Patients were recruited from the Psychiatry outpatient clinic of Hospital de Braga (Portugal) and interviews occurred at the end of patients' clinical contacts, from May 2018 to September 2018. Age, gender and educational level matched controls were recruited from the community. Control subjects were invited to be interviewed at the School of Medicine, University of Minho, Portugal, from July to September 2018.

Pre-established exclusion criteria for both groups comprised having neurological symptoms, having drug-related disorders, and being more than 65 years old or less than 18 years old. For the control group, suffering from any psychiatric disorder was also an exclusion criterion. The inclusion criteria for the OCD group were receiving psychiatric care at the Hospital of Braga and having OCD diagnosis. A semi-structured interview based on Diagnostic and Statistical Manual of Mental Disorders, Fifth Edition (DSM-5), was conducted to establish the OCD diagnosis and exclude the presence of any other comorbid psychiatric disorders. All individuals were Portuguese native speakers.

2.2. Procedures

In this study, we used the same protocol as used in Mota et al. (2017) (Mota et al., 2017). Each subject underwent an individual audio-recorded standard interview, composed of six reports. The interview began with a request to produce a "dream report" (either recent or remote). Next, the participants were requested to report "the oldest memory" they could retrieve in that moment. Then, the subjects were invited to report on their previous day ("yesterday report"). Finally, they were exposed to three images presented on a computer screen, comprising a "highly negative image", a "highly positive image" and a "neutral image". The images utilized were from the International Affective Picture System (IAPS) database of affective images (LANG et al., 1993). Subjects were instructed to pay attention to each image for 15 s and then report an imaginary story based on it. Whenever the participant spontaneously stopped the report, he/she was incentivized to keep talking by general instructions like "please, tell me more about that", in order to complete at least a 30 s report. The entire report protocol took between 5 and 10 min to be completed.

The six audio reports from each subject were transcribed by the same investigator, in order to minimize inter-subject differences. Then, they were individually converted to directed graphs using SpeechGraphs® software (Mota et al., 2015). Examples of speech graphs are shown in Fig. 1. First, the number of words used was compared between groups using the 30 s-limited reports. Then, in order to control for verbosity differences, the other Speech Graph Attributes (SGA) were calculated from reports limited to 30 words.

2.3. Graph measures

Graph measures were automatically calculated using SpeechGraphs®. Overall, fourteen SGA were calculated, including: 2 general measures – Nodes (N) and Edges (E); 3 global measures – Density (D), Diameter (DI) and Average Shortest Path (ASP); 3 connectivity-related measures – Largest Connected Component (LCC), Largest Strongly Connected Component (LSC) and Average Total Degree (ATD); 5 recurrence-related measures: Parallel Edges (PE), Repeated Edges (RE), Loops of one node (L1), Loops of two nodes (L2) and Loops of three nodes (L3); and 1 segregation measure: Clustering Coefficient (CC) (Mota et al., 2012, 2015). All measures are detailed in Table 1. For exemplification purposes, LCC and LSC measures are also explored in Fig. 1A.

Previous studies showed the importance of using general attributes (N and E), short recurrence attributes (PE, RE, L1, L2 and L3), connectivity attributes (LSC and LCC) and graph size attributes (Diameter and ASP) when analyzing speech (Mota et al., 2015, 2017, 2018). Based on the previous works, we also analyzed only these SGA in the present study.

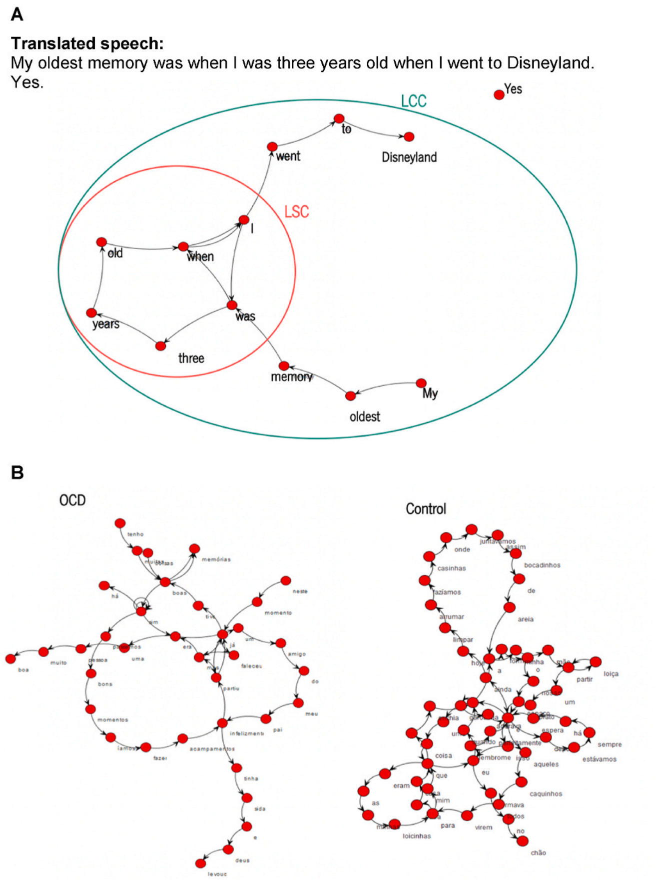

Fig. 1. Speech graphs examples. A) An example text of an old memory report represented as a speech graph. Green circle is the set of nodes in the largest connected component (LCC) and red circle is the set of nodes in the largest strongly connected component (LSC). **B)** Examples of speech graphs obtained from OCD and Control sample groups, in Portuguese language.

Table 1
Speech Graph Attributes (SGA): detailed description.

GENERAL
N: Number of nodes.
E: Number of edges.
GLOBAL
Density: number of edges divided by possible edges [D = 2*E/N*(N – 1)], where E is the number of edges and N is the number of nodes.
Diameter: length of the longest shortest path between the node pairs of a network.
Average Shortest Path (ASP): average length of the shortest path between pairs of nodes of a network.
CONNECTIVITY-RELATED
Largest Connected Component (LCC): number of nodes in the maximal subgraph in which all pairs of nodes are reachable from one another in the underlying undirected subgraph.
Largest Strongly Connected Component (LSC): number of nodes in the maximal subgraph in which all pairs of nodes are reachable from one another in the directed subgraph (node a reaches node b, and b reaches a).
Total Degree: given a node n, the Total Degree is the sum of "in and out" edges.
ATD (Average Total Degree): Average Total Degree is the sum of Total Degree of all nodes divided by the number of nodes.
RECURRENCE-RELATED
Repeated Edges (RE): sum of all edges linking the same pair of nodes.
Parallel Edges (PE): sum of all parallel edges linking the same pair of nodes given that the source node of an edge is the target node of the parallel edge.
Loop of one node (L1): sum of all edges linking a node with itself, calculated as the trace of the adjacency matrix.
Loop of two nodes (L2): sum of all loops containing two nodes, calculated by the trace of the squared adjacency matrix divided by two.
Loop of three nodes (L3): sum of all loops containing three nodes (triangles), calculated by the trace of the cubed adjacency matrix divided by three.
SEGREGATION
Clustering Coefficient (CC): It is a measure of the degree to which nodes in a graph tend to cluster together. Two versions of this measure exist: the *local* and the *overall level*. In this work we used the *overall level* measure as Clustering Coefficient (CC). Given a node n, the *local* clustering coefficient is given by a proportion of the number of links between the nodes within its neighborhood divided by the number of links that could possibly exist between them. The neighborhood of a node is defined as its immediately connected nodes. The *overall level* of clustering is measured as the average of the local clustering coefficients of all the nodes.

2.4. Psychometric scales

The Obsessive–Compulsive Inventory Revised (OCI-R) psychometric scale (Varela Cunha et al., 2022) was applied to OCD patients, and Yale–Brown Obsessive–Compulsive Scale (Y-BOCS) (Goodman, 1989) was filled by the patient's psychiatrist. The OCI-R is an 18-item self-report measure that uses a five-point Likert Scale that provides scores on six subscales (washing, checking, ordering, obsessing, hoarding, and neutralizing) and a total score. The Y-BOCS is a clinician-rating scale that assesses the severity of OCD symptoms, also comprising two subscales (obsession and compulsion) and a total score.

2.5. Statistical analysis

Statistical analysis was performed using IBM SPSS 26 software. The level of significance for the hypothesis tests (p value) was set at 0.05.

Groups were compared on the abovementioned SGA using independent t-student tests for variables that satisfied the assumptions of normal distribution and homogeneity of variance. Non-parametric Mann-Whitney tests were performed otherwise.

Additionally, correlation tests were performed in the OCD group between the psychometric scales and the SGA. All the correlations were performed using Spearman's rho correlation. The following SGA were used: N, E, PE, RE, LCC, LSC, L1, L2, L3, Diameter and ASP. The measures of OCD symptom's severity used were YBOCS-Total, YBOCS-Obsession, YBOCS-Compulsion, OCI-R-Total, OCI-R Washing, OCI-R Ordering, OCI-R Hoarding, OCI-R Checking, OCI-R Neutralizing and OCI-R Obsessing. As multiple tests of correlations were performed, Holm's Sequentially Rejective Bonferroni test was applied.

2.6. Ethical statement

The authors assert that all procedures contributing to this work comply with the ethical standards of the relevant national and institutional committees on human experimentation and with the Helsinki Declaration of 1975, as revised in 2013 (World Medical Association Declaration of, 2013). All procedures involving human subjects were approved by The Sub-commission of Life and Health Sciences of the University of Minho (SECVS) and by The Ethics Committee for Health of the Hospital of Braga (CESHB). Written informed consent was obtained from all subjects after the nature of the procedures had been fully explained.

3. Results and discussion

3.1. Sociodemographic and psychological characterization

The groups were matched by age, gender and completed school level. As shown in Table 2, no statistically significant differences were found between the groups in the sociodemographic data.

OCD patients were evaluated through OCI-R and Y-BOCS psychometric scales, and the complete characterization is available in Table 3. Total OCI-R score (self-reported) and total Y-BOCS score (psychiatrist-reported) showed a strong correlation (Spearman's rho = 0.71; $p < 0.01$).

Table 2
Demographic information of OCD and Control groups.

	OCD group	HC group	Statistics
N	39	37	–
Age *(Mean ± SD)*			U = 684.5; p = 0.704
	32.69 ± 13.31 (Min: 18; Max: 65)	33.65 ± 13.44 (Min: 19; Max: 64)	
Gender, N (%)			*X* (Hirschtritt et al., 2017) *(dF = 1, N = 76)* = 0.065; p = 0.799
Female	18 (46.2%)	16 (43.2%)	
Male	21 (53.8%)	21 (56.8%)	
Completed School level			*X* (Hirschtritt et al., 2017) *(dF = 5, N = 76)* = 1.148; p = 0.950
Illiterate	1 (2.6%)	0 (0%)	
4th grade	3 (7.7%)	3 (8.1%)	
6th grade	3 (7.7%)	2 (5.4%)	
9th grade	8 (20.5%)	8 (21.6%)	
12th grade	18 (46.1%)	18 (48.7%)	
University	6 (15.4%)	6 (16.2%)	

Table 3
Psychometric characterization.

Psychometric Scale	OCD group (Mean ± SD)
OCI-R	
OCI-R Total	30.74 ± 14.27
OCI-R Hoarding	4.08 ± 3.10
OCI-R Checking	5.64 ± 3.57
OCI-R Neutralizing	4.05 ± 3.40
OCI-R Obsessing	6.67 ± 3.95
OCI-R Ordering	5.74 ± 3.86
OCI-R Washing	4.13 ± 3.45
Y-BOCS	
Y-BOCS Total	22.92 ± 9.14
Y-BOCS Obsession	12.74 ± 4.54
Y-BOCS Compulsion	10.18 ± 5.07

3.2. Between-group comparison of reports using SGA

Firstly, the analysis was performed with time-limited reports of 30 s. Using this approach, only the word count (WC) was calculated and compared between groups, as the other SGA are verbosity-dependent and were calculated using word-limited reports.

Thus, regarding WC, OCD patients tend to produce smaller speeches than HC, although this finding was only significant for two reports: we found that OCD group spoke with fewer words (WC) in dream reports (U = 916.000; p = 0.043) and old memory reports (t = −2.802; p = 0.006). This result is congruent with a previous study focused on the vocal characteristics of OCD patients, which also showed that OCD patients have a lower speech rate (Cassol et al., 2010). The other reports failed to show significant differences in WC between groups, although they consistently show the same tendency (Fig. 2).

Then, the analysis was performed with reports limited to 30 words. Statistically significant differences between OCD and HC groups were found for some SGA during the dream report, as shown in Fig. 3. OCD group scored significantly lower in N (U = 853.000; p = 0.020) and LCC (U = 875.000; p = 0.010), and significantly higher in PE (U = 460.500; p = 0.034) and L2 (U = 483.000; p = 0.045).

These results suggest that OCD patients use a less diverse set of words (lower N) and have less connected speech (lower LCC). The lower connectivity of speech is also a finding reported in patients with schizophrenia, so it does not seem to be a specific finding in OCD (Mota et al., 2012, 2017). Moreover, the results indicate that OCD patients tend to repeat the same words and consequently have more short recurrences in their speeches (higher PE and L2) than HC. The increase in short recurrences in OCD patients is a new finding and could be framed in the psychopathology of OCD, either because of the possibility of rituals involving re-echoing words, or because of high levels of anxiety.

In fact, facing an anxiogenic situation, patients with OCD may present exacerbations of fears (such as fear of not pronouncing the words correctly or fear of making mistakes while speaking), as well as hesitation and intrusive thoughts of imperfection. All these thoughts and fears may justify the repetition of words and the lowering of speech connectivity. Importantly, these differences were only found when analyzing dream reports. We hypothesize that, as dreams have been considered to have an emotional regulation function (Levin and Nielsen, 2009; Scarpelli et al., 2019), recalling a dream may provide access to (conscious or unconscious) anxiogenic stimuli, exacerbating the described speech alterations. Indeed, deficits in emotional regulation have been extensively described in OCD (Ferreira et al., 2021; Picó-Pérez et al., 2022, de la Peña-Arteaga et al., 2022) and may contribute to these speech alterations. Our suggestion that dreams reports are especially informative about the differences of speech between OCD patients and HC is coherent with a previous study that also noticed the importance of dream reports when analyzing the speech of psychotic patients (Mota et al., 2015). In our perspective, this finding underlines the well-established importance of anxious stimuli in the eliciting of OCD symptoms.

On the other hand, one may hypothesize that cognitive impairments may justify the exacerbation of speech recurrence when the patient is faced with the incapacity to recall the dream. However, as we did not find the same results in the "old memory" reports analysis, we think that memory impairment does not completely justify our results.

As mentioned above, in contrast with the promising results regarding dream reports, the other five types of report failed to show significant differences between groups. Therefore, we consider that the structural analysis of speech does not unequivocally distinguish OCD patients from HC. Other previously published work that studied language in OCD also did not report any noticeable deficits in sentence construction, sentence repetition, dictation and writing skill in OCD patients (Ghahari et al., 2017). Thus, unlike schizophrenia and bipolar disorder, in which alterations of speech structure have been recurrently described (Mota et al., 2012; Low et al., 2020), the present study and previous ones indicate that there are no syntactic alterations in OCD. Regarding to this, we highlight the need for further studies to focus not only in the structure but also in the semantics of free speech.

3.3. Correlating SGA measures and psychometric scales in the OCD group

After Holm's Sequentially Rejective Bonferroni test for correction of multiple correlations, the present study failed to find correlations between SGA measures and the severity of clinician-reported symptoms (Y-BOCS scale) or self-reported symptoms (OCI-R scale).

3.4. Limitations and prospects

The main limitation of this study was the relatively small sample (39 OCD patients and 37 HC), which did not allow us to separate OCD patients according to their main symptom dimensions. This remains an open question for future studies, as we now hypothesize that different symptom dimensions may show different patterns of speech measures alterations. Replication in a larger sample will be an important future research direction. Furthermore, it might be interesting to evaluate not only different subgroups of symptomatology, but also different subgroups according to insight and other potential clinical sources of variability. Another limitation of this study is the potential influence of other psychiatric symptoms (such as anxious or depressive symptoms) was not controlled for. Even excluding patients with psychiatric comorbidities, these symptoms are often present in the OCD presentation and could have impacted our results.

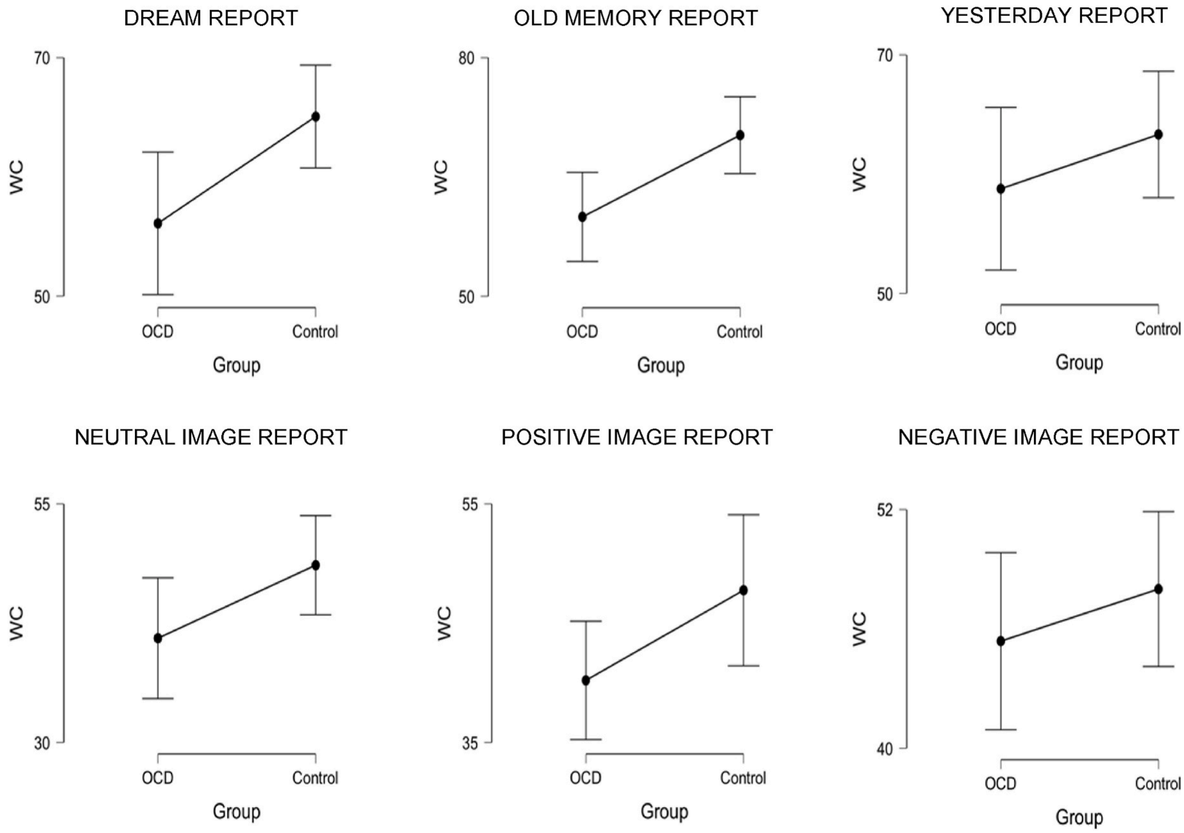

Fig. 2. Differences in the number of words spoken, using 30 s-limited reports. Except for Dream and Old Memory report, the reports did not show significant differences between groups: Yesterday report: $t = -1.061$; $p = 0.212$; Neutral image report: $t = -1.882$; $p = 0.064$; Positive image report: $t = -1.915$; $p = 0.059$; Negative image report: $t = -0.893$; $p = 0.375$.

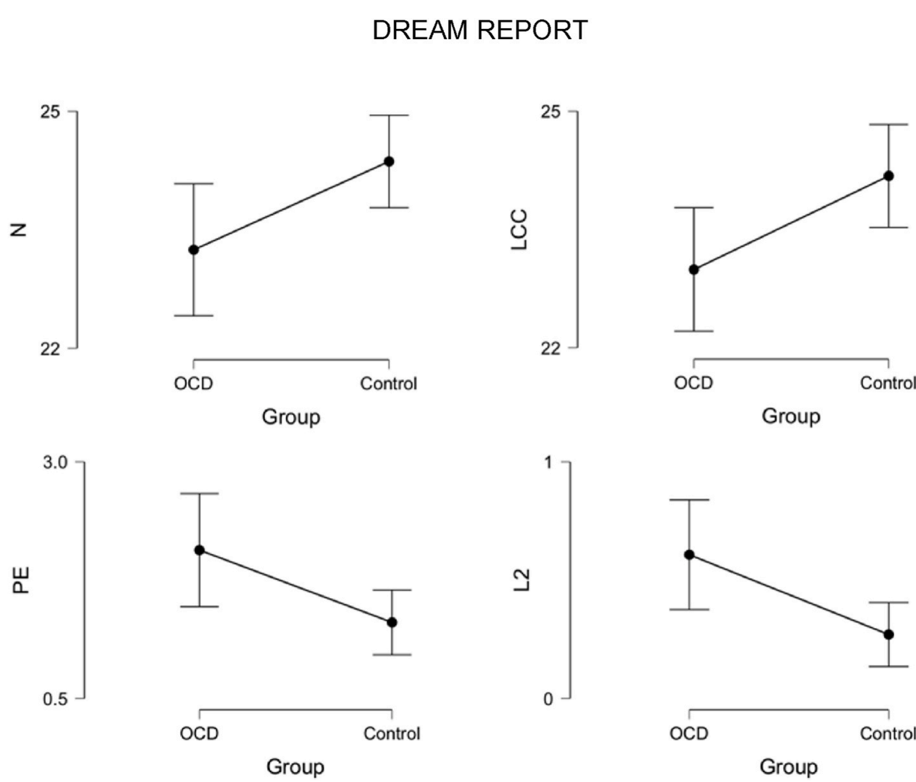

Fig. 3. Dream reports: differences between OCD and HC groups, using 30 words-limited reports.

To our knowledge, this is the first study analyzing the use of speech graphs in OCD. Consistent with previous studies, our results showed that dream reports were especially relevant when analyzing speech. However, the reasons behind this finding remain unclear as well as most aspects regarding dreaming phenomena.

Contrariwise to previous literature concerning psychotic disorders, and since most reports failed to show differences between OCD and HC groups, the present study failed to support speech structure analysis as a promising complementary tool in OCD diagnosis, although it remains to be explored whether this tool could be particularly useful in specific OCD subgroups (based on symptom subgroup or level of insight). Moreover, semantic analysis may be more promising than structural analysis in OCD, deserving further investigation in the future.

Author statement

Matilde Gomes: Methodology, Formal analysis, Investigation, Writing - Original Draft.

Maria Picó Pérez: Methodology, Formal analysis, Investigation, Writing - Review & Editing.

Inês Castro: Investigation.

Pedro Moreira: Methodology, Formal analysis, Investigation, Writing - Review & Editing.

Sidarta Ribeiro: Conceptualization, Methodology, Writing - Review & Editing.

Natália B. Mota: Conceptualization, Methodology, Formal analysis, Writing - Review & Editing.

Pedro Morgado: Conceptualization, Methodology, Investigation, Writing - Review & Editing, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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