Title: STRUCTURAL DIFFERENCES BETWEEN NON-LUCID, LUCID DREAMS AND OUT-OF-BODY EXPERIENCE REPORTS ASSESSED BY GRAPH ANALYSIS

Abbreviated title: Structural differences in dream experiences

Francisco T Gallo[1,2*], Ignacio Spiousas[2,3,4], Nerea L Herrero[1,2], Daniela Godoy[2,5], Antonela Tommasel[2,5], Miguel Gasca-Rolin[6], Rodrigo Ramele[7], Pablo M Gleiser[8#] & Cecilia Forcato[1#]

# Contributed equally

1 Laboratorio de Sueño y Memoria, Departamento de Ciencias de la Vida, Instituto Tecnológico de Buenos Aires (ITBA), Iguazú 341, (1437) Capital Federal, Buenos Aires, Argentina.

2 Consejo Nacional de Investigaciones Científicas y Tecnológicas (CONICET), Godoy Cruz 2290, (1425) Capital Federal, Buenos Aires, Argentina.

3 Sensorimotor Dynamics Lab (LDSM), CONICET, Universidad Nacional de Quilmes, Bernal, Argentina.

4 Laboratorio Interdisciplinario del Tiempo y la Experiencia (LITERA), CONICET, Universidad de San Andrés, Victoria, Argentina.

5 Instituto Superior de Ingeniería de Software Tandil (CONICET/UNCPBA), Tandil, Bs. As., Argentina.

6 Asociación Internacional de Onironautas. Carmelo Betore Bergua 2 casa 6 9c, (50014) Zaragoza, Spain.

7 Centro de Inteligencia Computacional, Instituto Tecnológico de Buenos Aires (ITBA), Iguazú 341, (1437) Capital Federal, Buenos Aires, Argentina.

8 Laboratorio de Neurociencia de Sistemas Complejos, Departamento de Ciencias de la Vida, Instituto Tecnológico de Buenos Aires (ITBA), Iguazú 341, (1437) Capital Federal, Buenos Aires, Argentina.

Corresponding author:

Francisco Gallo, frgallo@itba.edu.ar

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Author contributions

FTG, CF and PMG made substantial contributions to the conception and design of the work. FTG performed the research. NLH, and FTG acquired the data. DG and AT processed the text, created the graphs and calculated the graph attributes. FTG and CF wrote the paper. IS and FTG did the statistical analysis. FTG, MG, RR, PMG and CF contributed to revising it critically. CF and RR contributed in funding acquisition and CF contributed in project administration.

Abstract

In this study, we examine the structural properties of dream reports that include non-lucid, lucid dreams (LDs) and out-of-body experiences (OBEs). We collected a set of 916 dream reports (728 non-lucid dreams, 122 LDs, 68 OBEs) obtained from 60 participants that kept a dream journal for two months. The collected reports were transformed into directed graphs, where each different word plays the role of a node, and consecutive words are connected by a directed, unweighted edge. We analyzed different network measures to compare the graphs. Overall, correlations between graph attributes and the number of nodes revealed that OBEs showed a negative slope for diameter and ASP, which was not observed in non-LDs or LDs. The slope for betweenness centrality also had a pronounced effect in OBE dreams. These results suggest that OBEs may have unique structural properties compared to other types of dreams, which could provide insight into their nature and potential role in human consciousness. These findings suggest that OBE dreams may have a more coherent and unified narrative, with certain nodes playing a more central role in the overall network.

Key words: Lucid dreams, Out-of-body experiences, Graph analysis, Dreams

1. Introduction

Dreaming is a complex and intriguing phenomenon that occurs during sleep (Siclari et al., 2013). Evaluating conscious experiences, especially those of dreams, can be challenging as they are inherently subjective and cannot be directly observed. To understand the nature of dreaming, researchers must rely on the retrospective reports of individuals after they have awakened (Rosen; 2013). Among the various forms of dreams, two types of conscious dream experiences have received particular attention: lucid dreams (LDs) and out-of-body experiences (OBEs). LDs are characterized by the presence of certain qualities of consciousness, such as awareness within the dream environment (Holzinger & Mayer, 2020; Laberge, 2010), while OBEs are characterized by the sensation of being "outside" the physical body and viewing the world from that perspective while still being aware (Sheils, 1978; Blackmore, 1982; Irwin, 1988; LaBerge et al., 1988; de Sá and MotaRolim, 2016; Herrero et al., 2022; Cheyne, 2003). The relationship between LDs and OBEs has been a topic of interest, but the distinction between the two is still not clear due to limited physiological measures (Yu & Shen, 2020; Holzinger & Mayer, 2020).

There are at least two types of analyses that have been used to study dreams. One of them includes the analyses of the content (Domhoff, 1996) and the other involves graph theory analysis (Mota et al., 2014). The latter represents speech as a graph and calculates mathematical qualities that quantify local and global topological characteristics of the reports. It has shown to be effective in differentiating dream reports in patients with psychosis such as schizophrenia and bipolar disorder (Mota et al., 2012; Mota et al., 2014) as well as in differentiating NREM and REM dream reports (Martin et al., 2020).

Here, in order to better understand the differences and similarities between LDs and OBEs, we performed an exploratory analysis using graph theory to compare the reported experiences. For that, dream reports were collected from 60 individuals and divided into three groups based on their history of lucid dreaming and OBE: non-lucid dreamers, who had never experienced either LDs or OBEs; lucid dreamers, who had experienced LDs but not OBEs; and OBE dreamers, who had experienced both LDs and OBEs. The dataset included 916 reports (728 non-lucid dreams, 122 LDs, 68 OBEs). The reports were presented as directed graphs, with each word serving as a node and consecutive words connected by a directed, unweighted edge. Graph theory was used to analyze the overall structure of the reports.

2. Materials and Methods

This study presents an analysis of a dataset previously collected by our research team at the Sleep and Memory Lab from the Instituto Tecnológico de Buenos Aires (ITBA) (Gallo et al., 2023).

2.1 Dream journal and classification.

In the original data collection effort, participants recorded their dreams for two months, noting the time, date, level of awareness, and description of each dream, as well as how they became lucid (if applicable). Dreams were classified by two independent experimenters based on descriptions provided in a journal. A dream was considered lucid if the dreamer was aware, either directly or indirectly. An OBE was identified if the dreamer described leaving the body or reported an aura (reported in Herrero et al., 2022). Vague or unspecific reports were discarded, leaving a sample of 916 dreams (731 non-LDs, 117 LDs, and 68 OBE dreams).

2.2 Text processing and analysis

The text of dream reports was processed using Natural Language Processing (NLP) techniques in order to prepare it for sentiment and conceptual analysis. The spaCy library (https://spacy.io/) with pre-trained language models for Spanish was used for language processing. Tokenization was performed to split the text into meaningful elements called tokens or words. Part-of-speech (POS) tagging was then carried out to mark the words in the text as corresponding to a specific part of speech (noun, verb, adjective, etc.) based on their context in a given sentence. The final step of this process was lemmatization, which groups different inflected forms of words into a single element, known as the lemma or dictionary form. This way, words that have the same lemma can be analyzed together as a single concept despite their different inflections or derivations of meaning. Once text processing was performed, a graph was built for each dream considering the entire text of the dream report. The nodes in the dream graphs were lemmas of the original words, and edges were established for words occurring consecutively in the text. Only lemmas corresponding to words with the POS tags NOUN, VERB, and ADJ were included in the graph construction, as these words contribute to content description.

2.3 Speech graph attributes.

A graph is a mathematical representation of a network with nodes linked by edges, formally defined as G = (N, E), with the set of nodes N = {w1, w2, . . ., wn} and the set of edges E = {(wi,wj)} (Mota et al., 2012, 2014; Bertola et al., 2014). A speech graph represents the sequential relationship of spoken words in a verbal report, with each word represented as a node, and the sequence between successive words represented as a directed edge (Mota et al., 2012, 2014; Bertola et al., 2014). A total of 14 speech graph attributes (SGA) were calculated for each dream report, comprising general graph attributes (N, total of nodes; E, total of edges), recurrence (PE, parallel edges; RE; L1, L2, and L3, loops of one; two and three nodes), connectivity (LSC, largest strongly connected component) and global attributes (ATD, average total degree; Density, Diameter; average shortest path (ASP); CC, clustering coefficient; see Mota, 2012 for details).

2.4 The co-occurrence networks were constructed using KH coder 3 software (Higuchi, 2016) to visualize the relationship between the most frequent words in the text corpora of three types of reports: NN, LL, and OO. To ensure the resulting network is easy to read, the methods developed by T. M. J. Fruchterman & E. M. Reingold (1991) and T. Kamada & S. Kawai (1988) were used to determine word locations. In this process, terms that frequently appear together were connected to illustrate the co-occurrence structure in the data. The co-occurrence network was constructed based on the adjacency of two word forms in sentence formation. The resulting networks provide a visual representation of the most frequent words and their relationships in the text corpora of three types of reports.

2.5 Data exclusion

We removed outliers by comparing mean values for number of nodes and edges per participant and dream type, and used the *Routliers* R package (Leys et. al., 2013; Delacre & Klein, 2019) to remove data points more than 3 MADs from group median. This filtered out participants reporting exceptionally long or short dreams. After exclusion, we had 42 non-lucid, 26 lucid, and 11 OBE dreamers, down from 57, 31, and 16 respectively.

2.6 Statistical analysis.

We fitted weighted linear models to estimate the associations of the graph's features with the type of dreamer for both type of dreamer (non-LDs comparisons) and type of dreams (typical dreams comparisons; Figure 2). We use weighted models instead of plain ones since there is an unbalanced number of dreams per dreamer. To take this into account without overweighting the dreamers with more dreams we weighted the data for the model fit with the logarithm of the number of dreams (log(N+1)). We also fitted weighted linear models to estimate the associations of two of the graph's features and the type of dreamer or the type of dream. For example, when modeling the Number of nodes vs diameter for the non-LDs we fitted a full model with the Number of nodes as the dependent variables and the diameter and type of dream and its interaction as the independent variables. We use the *lm* function of base R that allows us to fit weighted linear models via the parameter *weights*. The parameter estimates and confidence intervals were calculated using the broom package in R (Robinson et al., 2021). We tested the fixed effects of both models with an F-test using the Anova function of the car R package (Fox & Weisberg, 2018).

3. Results

We first lemmatized and transformed each dream report into a graph and calculated its connectivity, recurrence and global attributes (Figure 1). We found no significant differences between NN, LL and OO reports for any of the analyzed variables (Figure 2, supplementary tables 1) except for diameter, with NNs having a smaller diameter than LLs, no other differences were observed between the groups ($F(2, 37) = 3.32$, $P = 0.047$, multiple comparisons: $P_{OOvsNN} = 0.26$, $P_{OOvsLL} = 0.67$, $P_{NNvsLL} = 0.049$). However, there were significant differences in some of the attributes when comparing NN, NL, and NO reports. Specifically, the NO reports had a lower number of nodes ($F(2, 52) = 3.95$, $P = 0.025$, multiple comparisons: $P_{OOvsNN} = 0.48$, $P_{OOvsLL} = 0.019$, $P_{NNvsLL} = 0.34$) although the total number of words were no significant between conditions (NN: 217.3 ± 53.2 words, NL: 234.5 ± 44.4 words, NO: 169.7 ± 46.3 words; $F = 2.15$, $P = 0.12$; multiple comparisons: $P_{NNvsNL} = 0.87$, $P_{NNvsNO} = 0.37$, $P_{NLvsNO} = 0.11$). Moreover, the NO reports had a lower number of edges and LSC when compared to NL reports. However, we did not find any differences between NN and NL or between NN and NO reports (Edges: $F(2,52) = 3.87$, $P = 0.027$, multiple comparisons: $P_{NOvsNN} = 0.49$, $P_{NOvsLL} = 0.020$, $P_{NNvsNL} = 0.34$; LSC: $F(2,52) = 4.37$, $P = 0.017$, multiple comparisons: $P_{NOvsNN} = 0.39$, $P_{NOvsNL} = 0.012$, $P_{NNvsNL} = 0.34$). We found that NO graphs had a significantly higher density than the NL graphs, however, we did not find any differences between NN and NL or between NN and NO reports ($F = 3.20$, $P = 0.048$; multiple comparisons: $P_{NOvsNN} = 0.55$, $P_{NLvsNO} = 0.038$, $P_{NNvsNL} = 0.41$). No further differences were found for average neighbor degree, parallel edges, loops of 1, 2 nor 3 nodes, betweenness centrality or clustering (supplementary table 1).

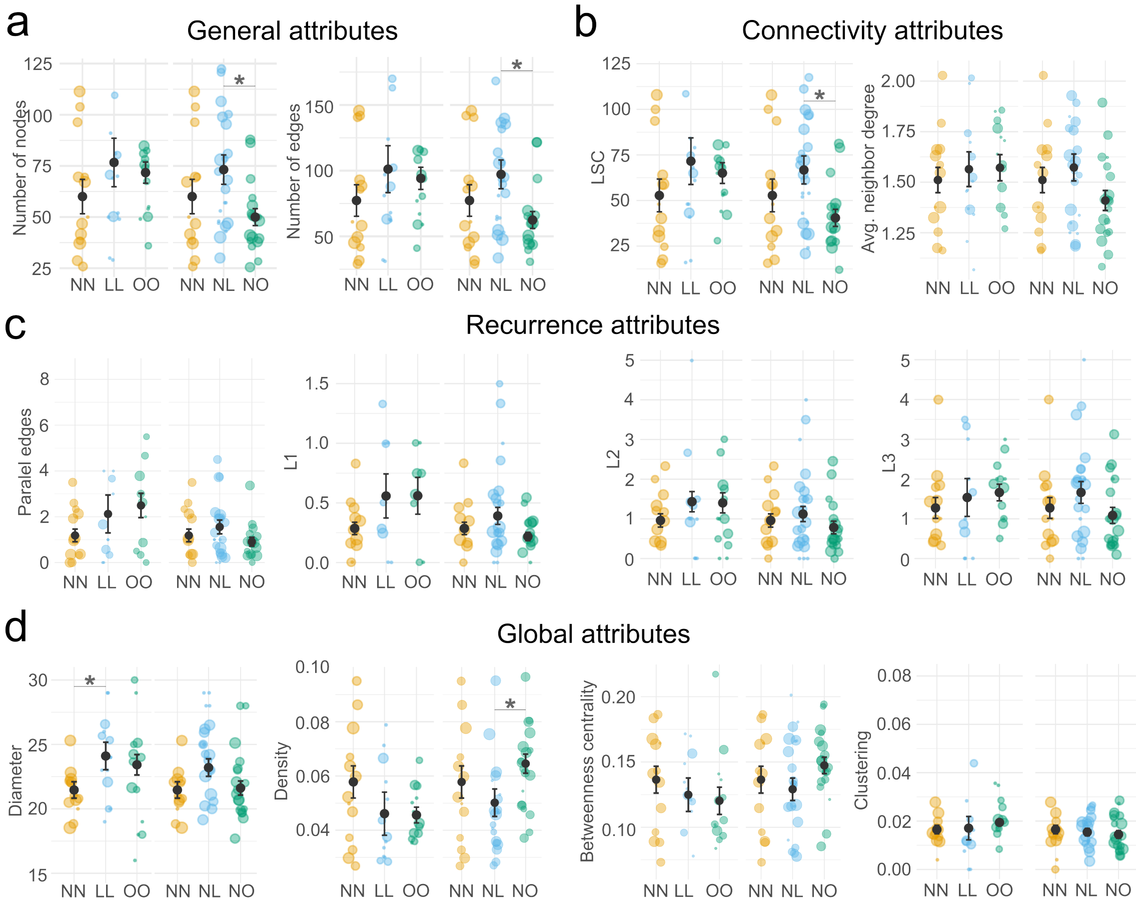

Figure 1. **Network Analysis of Dream Reports**. **a**. General attributes including number of nodes and edges. **b**. Connectivity attributes, including number of nodes on the largest strongly connected component (LSC) and average neighbor degree. **c**. Recurrence attributes, including number of parallel edges (PE) and number of loops with one, two or three nodes (L1, L2, L3). **d.** Global attributes, such as diameter, density, betweenness centrality and clustering. Asterisks show P-values for the F-test, *: $P < 0.05$ (supplementary table 1).

Due to the differences in the number of nodes across graphs, we performed linear models analysis to study if there were any variations in the relationships between node and edge attributes and other variables depending on the type of dream being considered (Figure 2).

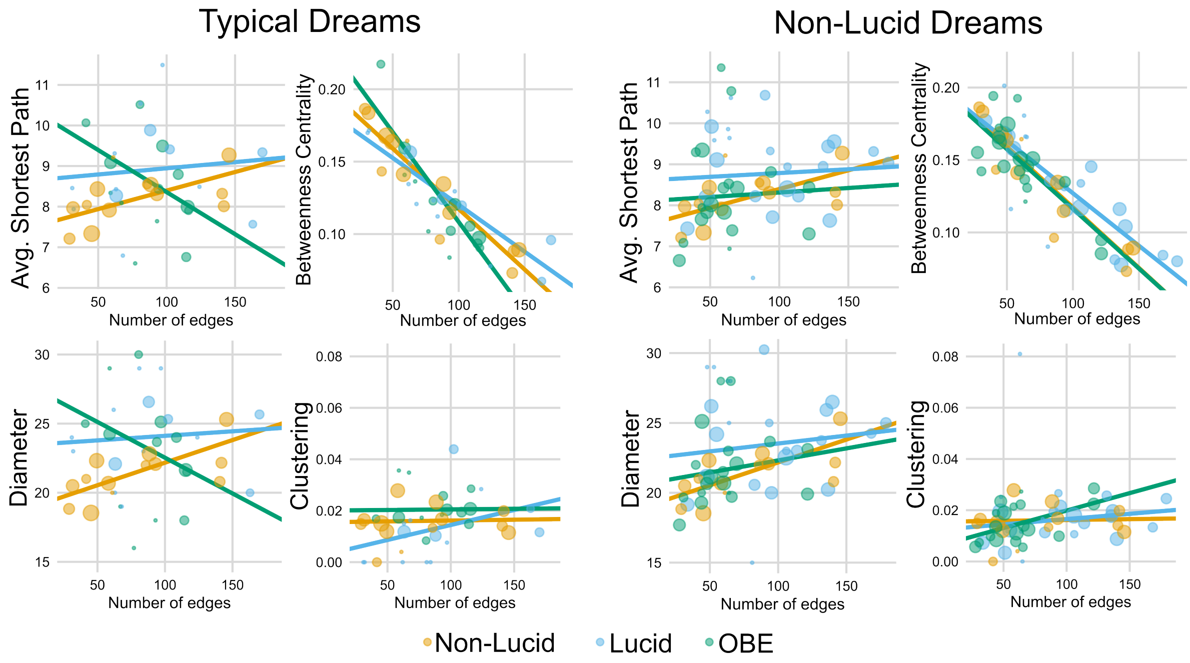

Figure 2. Correlation of Network Attributes. This figure displays the comparison between typical dreams (left) and non-LDs (right) through the fitting of linear models. Here we examine the relationship between the number of edges (nodes in text) with other network attributes such as diameter, clustering, average shortest path, and betweenness centrality.

Regarding the typical dreams (NN, LL and OO), we observed that there was a significant effect of the type of dream on the associations between ASP and edges, but not between ASP and nodes (edges: $F(2,34) = 3.45$, $P= 0,043$; nodes: $F(2,34) = 2.27$, $P = 0.11$). Furthermore, when observing the fitted slopes, we found that the slope for OO was negative (edges: slope $= -0.021$, $t(34) = -2.62$, $P = 0.012$; nodes: slope $= -0.024$, $t(34) = -2.13$, $P = 0.04$), while the slopes for NN and LL were positive (edges: NN slope $= 0.009$, $t(34)= 1.98$, $P=0.055$; LL slope $= 0.003$, $t(34)= -0.74$, $P = 0.46$; nodes: NN slope $= 0.014$, $t(34)= 2.11$, $P=0.041$; LL slope $= 0.0098$, $t(34)= -0.35$, $P = 0.72$). Regarding betweenness centrality, which measures the centrality of a node in a network based on the number of shortest paths that pass through it, there was also a significant effect of the type of dream for the association with nodes/edges (nodes: $F(2,34) = 4.21$, $P = 0.023$, edges: $F(2,34) = 3.87$, $P = 0.03$). In addition, the slope for OOs reports had a more pronounced negative slope than LLs and NNs (edges: NN slope = -0.0008, $t(34)= -10.54$, $P < 0.0001$; LL slope: -0.0006, $t(34) = 1.34$, $P = 0.18$, OO slope: -0,0012, $t(34) = -2.06$, $P =0.046$; nodes: NN slope = -0.0012, $t(34)= -10.37$, $P < 0.0001$; LL slope: -0.0009, $t(34) = 1.13$, $P = 0.26$, OO slope: -0.0019, $t(34) = -2.38$, $P = 0.022$). Regarding diameter, there was no significant effect of the type of dream for the association with nodes/edges (nodes: $F(2,34) = 1.80$, $P = 0.17$, edges: $F(2,34) = 3.04$, $P = 0.06$). Although, similar to ASP, the OOs slope showed a negative association with the number of edges (OO slope = -0.051, $t(34) = -2.416$, $P = 0.021$; NN slope= 0.032, $t(34)= 2.13$, $P = 0.027$; LL slope = 0.059, $t(34) = -1.04$, $P = 0.30$) and nodes (OO slope = -0.054, $t(34) = -1.87$, $P = 0.069$; NN slope= 0.049, $t(34)= 2.39$, $P = 0.022$; LL slope = 0.023, $t(34) = –0.68$, $P = 0.49$). It is important to highlight that the ASP and diameter are measures of network communication efficiency and size, respectively. Therefore, the increase in the number of nodes and/or edges in OBE dreams led to a decrease in diameter and ASP, in contrast to what was observed in NN and LL. Regarding the clustering, there was no significant effect of the type of dream for the association with nodes/edges (nodes: $F(2,34) = 0.97$, $P = 0.38$, edges: $F(2,34) = 0.93$, $P = 0.40$).

Interestingly, we observed a different profile for the non-lucid dreams. We observed that for any of the attributes there was significant effect of the type of dream on nodes or edges (ASP, nodes: $F(2,49) = 0.30$, $P = 0.73$, edges: $F(2,49) = 0.50$, $P = 0.61$; between centrality, nodes: $F(2,49) = 0.30$, $P = 0.73$, edges: $F(2,49) = 0.45$, $P = 0.63$; diameter, nodes: $F(2,49) = 0.29$, $P = 0.74$, edges: $F(2,49) = 0.48$, $P = 0.61$; clustering, nodes: $F(2,49) = 1.01$, $P = 0.37$, edges: $F(2,49) = 1.01$, $P = 0.37$).

We further performed a qualitative analysis to identify common themes and patterns across different types of dreams (Figure 3). The words "see" (*ver*) and "home" (*casa*) were most common across all dream reports, while "remember" (*recordar*) stood out in lucid dreamers' reports and "person" (*persona*) in OBE dreamers' reports. "Dream" (*sueño*) was prominent in both lucid and OBE dreams' reports. When observing the reports of typical dreams, that is the non-lucid dreams of non-lucid dreamers (NN), the lucid dreams of lucid dreamers (LL) and the OBE dreams of OBE dreamers (OO), the frequency of the word "dream" (*sueño*) was the main difference between LL and OO, being higher in LL reports. This goes in line with previous studies showing that people who experienced OBEs, usually consider that it is not a dream but the veridical reality (Blackmore, 1982; Herrero et al., 2022). The terms "body" (*cuerpo*), "to leave" (*salir*), and "to feel" (*sentir*) were frequently used in OO reports but not in other types of dreams.

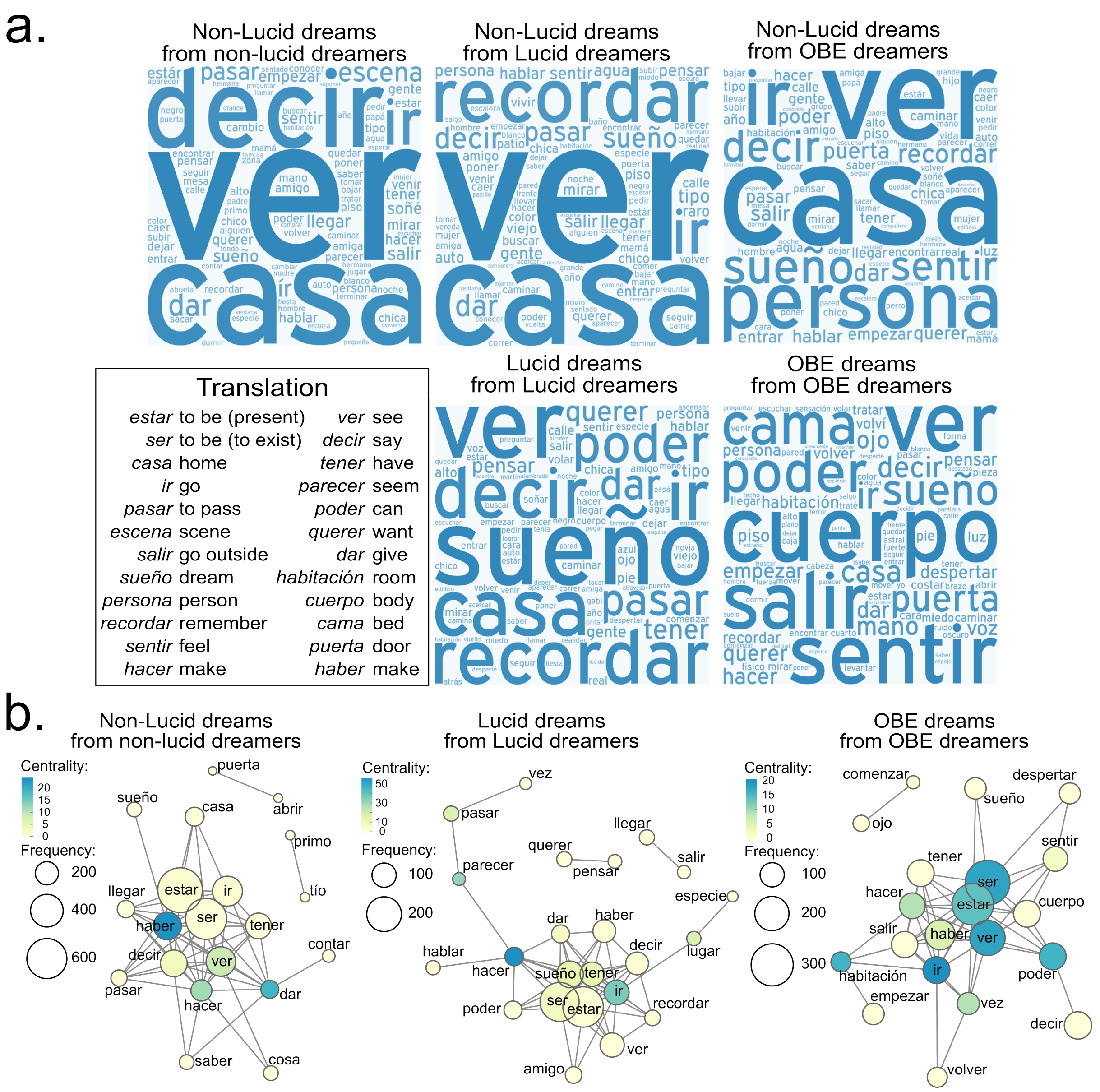

Figure 3. Dream Report Word Clouds and Co-occurrence Networks. a. Word Clouds of the Most Frequent Terms. This figure displays word clouds of the 100 most common terms in the lemmatized vocabulary of all dream reports analyzed in this study; all word clouds were generated using http://www.wordart.com. **b**. Co-occurrence Networks of Dream Reports. This figure presents co-occurrence networks constructed for the original text corpora of three types of typical dream reports. Co-occurrence refers to the adjacency of two words in sentence formation.

To visualize the general associations between the most frequent words, we constructed co-occurrence networks (Figure 3; adjacency of two word forms in sentence formation) for the original text corpora for three types of reports (NN, LL and OO). For the NN reports, the most central words were “have” (*haber*), “give” (*dar*), “do” (*hacer*) and “see” (*ver*); for LL reports were “do” (*hacer*), “go” (*ir*), “dream” (*sueño*) and “have” (*haber*); and for OO reports were “to be” (*ser*), “see” (*ver*), “go” (*ir*), “room” (*habitación*), “can” (*poder*), “do” (*hacer*) and “being” (*estar*). Most notably, in the OO networks, among the most central words were "to be/to exist" (*ser*) and "to be/to be present" (*estar*), which were also the most frequent words in OO.

4. Discussion

We here found that OBE dreams are different experiences than lucid and non-lucid dreams. We observed that only for the OO reports, the higher the number of nodes (or edges), the less the diameter and the average shortest path. This suggests that as the OBE reports increase in length they do not include new words into the narrative. On the contrary, OBE dreams would have a more coherent and unified narrative, rather than one with many disparate or unrelated scenes or events. Thus, a dream with a more compact and efficient network structure would likely have fewer distinct elements or themes and more connections or relationships between those elements.

Furthermore, we found qualitative differences between OBE, LD and non-LD reports. We observed that there were words such as “see”, “home” and “say” that were common to all the dream reports while other words were more prominent in specific types of dreams. For example, “remember” was more prominent in lucid as well as in non-lucid dreams of the lucid dreamers. This could be due to the fact that lucid dreamers are usually trained to remember to do something when they acquire consciousness during a dream. We suggest that as lucid dreamers, before going to sleep, planned to remember to become lucid while they are sleeping, the word "remember" could be easily incorporated into a non-lucid dream by ordinary memory processes such as memory reactivation and integration (Malinowski y Horton, 2014; Stickgold et al., 2000). That is, recently acquired information is reactivated and integrated during sleep (Rash & Born, 2013) and these memory processes could give rise to our dream content (Wamsley & Stickgold, 2018). Thus, waking experiences as well as hypnagogic instructions can be easily incorporated into dream content (Haar Horowitz et al., 2020).

Interestingly, the frequency of the term "dream" differed between LL and OO reports. This result supports the notion that people who experienced OBE report the episodes as an extremely vivid experience, with the perceptual qualities of veridical perception (Blackmore, 1982) and they usually consider that they are not dreaming (LaBerge & DeGracia, 2000). We also found that the words "body," "to leave," and "to feel" were prominent in OBE dreams but did not appear in any other type of dream. All these words are directly related to the OBE episodes where the dreamers usually perceive like they leave their physical body (Blackmore, 1982). The co-occurrence networks for the dream reports showed that only for the OO networks the most frequent words coincided with the most central ones. This could be due to the increased recurrence of the OBE reports that is also evidenced in Figure 2, showing that the higher the number of nodes (or edges) the less the diameter and the ASP.

Additionally, the betweenness centrality of the networks in OBE dreams showed a more pronounced negative trend in relation to the number of nodes compared to non-LDs and LDs. This finding suggests that OBE dreams have a more specialized network structure, characterized by certain nodes playing a more central role in the overall network. These nodes may have a greater influence on the structure and content of the dream narrative.

In contrast, non-LDs and LDs displayed a less pronounced negative trend in relation to the number of nodes, indicating that these types of dreams may have a more diffuse network structure with fewer central nodes.

Regarding the graph attributes analysis, we did not reveal any significant differences between typical dreams (NN, LL and OO, Figure 1). It is worth noting that these attributes are typically utilized to compare more extreme cases rather than subtle differences between dream narratives. As such, correlations between certain attributes and the number of nodes were performed to examine whether any effects were more noticeable in these relationships rather than in means. However, graph attributes analysis reveal significant differences for non lucid dreams. That is, the NO displayed a lower number of nodes, edges, and nodes on the largest strongly connected component (LSC) compared to the NL. Additionally, the NO had fewer unique words but a higher density of connections than NL. One possible explanation for this, could be attributed to a greater focus of the OBE subjects on writing about conscious experiences rather than NO, as the total number of words between non lucid dreams remain constant between dreamers (NN, NL, NO).

To sum up, graph analysis has shown promising potential in studying subjective experiences and can reveal subtle differences between LDs and OBEs. The findings suggest that OBEs may have a more tightly knit structure compared to LDs and non-LDs, which could provide valuable insights into the nature of these experiences.

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