Stoned Out Loud: Variability in Thought Dynamics During Cannabis Experience

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ABSTRACT

A thought refers to a mental state or a sequence of mental states along with transitions that bring about these mental states[1]. Fluctuations in transitioning from one mental state to another over time can manifest in a narrow manner, with focus on a single topic (low variability), or in a broader and more random fashion, containing leaps from one subject to an entirely new one (high variability). The intricate nature and evolution of human thought, especially in relation to consciousness, has intrigued scholars from ancient philosophers to modern psychologists. However, variability in thought dynamics, particularly under the influence of substances like cannabis, has not yet been examined empirically. With its rapid legalization, studying the effects of cannabis on cognitive processes is imperative. This study explores the potential shifts in thought processes due to the influence of cannabis with the help of the think aloud paradigm (TAP) model established by Raffaelli[2] and network science approaches for quantitative analysis. Each participant is administered two 90-minute session, one sober, and another under the influence of cannabis. The TAP task is a 12-minute block during which participants are asked to verbalize their thoughts out loud. Results from analyzing the sober and smoking conditions cooccurrence network measures showed a notable decline in word count, number of nodes, and number of edges in the smoking condition. Other measures, such as degree centrality and betweenness centrality, were also found to be significantly different between the two conditions. Furthermore, this study found the sequence of sessions (smoking first or sober first) as well as the task order to be non-influential.
Keywords: Cannabis, Thought Dynamics, Semantic Network, Think Aloud Paradigm

Introduction

The nature of human thought and how it interacts with consciousness has had philosophers captivated and debating for millennia. One of the earliest explorations of this interplay can be traced back to Plato's dialogue in "The Republic" around 375-380 BCE. Here, Plato articulated the distinctions between the ephemeral material realm and the domain of forms or ideas. According to him, thoughts can be understood as the recollection of these quintessential forms[3,4]. This conceptualization continued to evolve with philosophers likes René Descartes, and Immanuel Kant as well as with psychologists like Wilhelm Wundt[5–7]. Wundt proposed a methodological study of thoughts and psychological processes via introspection[7]. Introspection's primary limitation is that it is inherently subjective, making it hard to replicate and even harder to objectively examine[8]. Regardless of these limitations, it provoked a shift from philosophical discourse to systematic experimental study of thought processes[8,9]. Despite these seminal discourses from centuries ago, highlighting the significance of thoughts and their dynamics, the methodological advancements have not progressed enough to provide substantial empirical insights regarding thought dynamics. This has resulted in knowledge gaps regarding potential variabilities in thoughts during rest or under external influences that affect cognitive abilities like decision making (i.e.

psychoactive drugs).

Within the complex domain of cognition, thoughts are a sequence of mental states along with transitions that bring about these mental states[1]. When a person is idle, not engaged in any tasks, and not provided with any prompts, their thoughts during this state of rest could offer unique insights into the internal workings of their cognitive architecture that could serve as a reflection of their current and future mental states[2,10]. A stream of thoughts could either have less variability and revolve around or be directed towards a singular theme, or it could be expansive, covering a myriad of topics and possibilities introducing more variability. Such variability in thought content could potentially be influenced by external modulators of cognition like cannabis[11].

Cannabis has long been used for its recreational allure as well as its medicinal properties and hence piqued scientific interest due to its effects on the brain. Although cannabis intoxication experience varies among individuals, anecdotal accounts from users often suggest feeling euphoric or relaxed and shifts in the nature of their thoughts[12,13]. Beyond this, it has been shown to interact with one's cognitive abilities like perception, memory, decision-making, regulating emotions and behavior, mind wandering, and divergent thinking[11,14,15]. Additionally, the main psychoactive component in cannabis, Δ^9-tetrahydrocannabinol (THC), has been shown to affect brain structures involved in cognitive and emotional processes, as well as introspective awareness[16,17]. However, the scientific study of whether and how cannabis intoxication shifts the nature and course of thoughts at rest remains unexplored. Given the increasing legalization of cannabis for recreational use across the globe and its growing medicinal applications, studying its influence on thought dynamics can help set effective guidelines for its safe use and in determining appropriate doses for therapeutic and medicinal applications.

Experimental methodologies for studying thoughts have long been dominated by traditional approaches like experience sampling, daily diary, self-recording, and retroactive recall[18,19]. Although effective to a certain extent, combining such approaches with more robust analytical tools has the potential to uncover nuanced insights about these intricate thought processes. The think aloud paradigm (TAP) task has been used in the past to study autobiographical memory, future thought, and confabulation[20–22]. More recently, it has gained more popularity for its potential in studying unprompted thoughts as this approach provides a window into real-time cognition[2,23–25]. However, this approach generates vast amounts of qualitative and quantitative data per subject, which can be challenging to analyze in an objective and systematic manner. Therefore, this study employs the TAP model established by Raffaelli[2] along with network science approaches to analyze the potential influence of cannabis on the variability in thought dynamics. Network science has been extensively used in various fields to understand social dynamics, the structure of languages, and to quantify the structure of cognitive representation to examine its influence on cognitive processes like creativity and memory retrieval[26]. When used to analyze self-generated thought data, network science offers a qualitative visual representation of the trajectory of thoughts over time, revealing the interplay between different themes in the thought content. Furthermore, it has the potential to quantify the variability in thought dynamics, which bridges the gap between the quantitative nature of scientific analysis and the qualitative nature of thoughts.

Considering this backdrop, the purpose of this study is to explore whether the consumption of cannabis in a naturalistic setting influences the dynamics of thought patterns and if there are any discernible changes in the variability of these thoughts during the cannabis experience. One study has shown an increase in mind wandering, suggesting a decrease in attention capabilities under the influence of cannabis[14]. This would lead us to speculate that cannabis could increase the variability in thought patterns. However, another study has shown cannabis to decrease divergent thinking[15]. Since the very nature of divergent thinking is related to highly variable thoughts, it could mean that cannabis would decrease the variability in thoughts. Therefore, due to the lack of definitive literature on the specific effects of cannabis on thought dynamics, this study adopts an exploratory stance, employing network science and a naturalistic cannabis administration paradigm to address this knowledge gap.

Methods

Participants

The study sample comprised 48 self-selected participants (19 males and 18 females), aged between 19 to 49 years (Mean = 25.57, Median = 22.00, SD = 8.30). Data from 11 participants were excluded due to data recording issues (n=9), or failure to abide by the task instructions (n=2). The remaining 37 participants were included in the subsequent analyses. Participant recruitment was done using a multi-modal approach that involved advertisements posted to online platforms (Reddit and LinkedIn), and displayed in and around the University of British Columbia's Vancouver campus to invite participation. Participants self-identified as regular cannabis users, having consumed cannabis at least once a week for the preceding 30 days. Participants were excluded from the study if they reported being pregnant, were receiving treatment for psychotic or bipolar disorder, or had regularly consumed nicotine within the last 3 months. These conditions constituted the study's exclusion criteria. Informed consent was secured from all participants prior to the study, and each participant was compensated 40 CAD, to acknowledge their time and contribution upon completing the study. The research methodologies and procedures strictly adhered to the relevant guidelines and regulations approved by the University of British Columbia's Institutional Review Board.

Procedure

The experimental design implemented in this study involved each participant attending two 90-minute online sessions via a secure video platform (Zoom)[27]. This research methodology adheres to the previously established Naturalistic Cannabis Administration Protocol (NCAP;[28]). Each session comprised of three tasks: the Think Aloud Paradigm (TAP), the Free Associations Semantic task (FAST), and a Time Reproduction task (TRT). Alongside these tasks, participants were asked several questions during and at the end of each session. To avoid any potential order effects, the experimental design was counterbalanced such that each participant was randomly assigned to one of two task sequence groups (TAP $\rightarrow$ FAST & TRP, or FAST & TRP $\rightarrow$ TAP). Additionally, each participant was randomly assigned to smoke cannabis in either their first session or their second. Each participant's second session was scheduled at least two weeks following the initial session but no later than three months.

Prior to a participant's initial session, a demographics questionnaire and a cannabis use questionnaire were administered[28]. Following this, each participant is instructed to have their cannabis ready (joint rolled, pipe packed etc.) prior to joining each session. They are also instructed to join the session from a private, distraction-free environment (chosen by the participant) and to consume the same quantity of cannabis as their typical usage during the smoking session (instructed to get "as high as you normally would"). At the start of each session, a trained research assistant (RA) reaffirmed participant consent, before reading out instructions for completing each of the three tasks during the session. Following this, participants completed a set of practice tasks on Pavlovia.org (using the Chrome browser), where the RA read the onscreen instructions to the participants. These practice tasks were intended to mitigate any potential technical difficulties that could arise during the actual session as well as to familiarize the participants with each task. The practice data were excluded from the subsequent analysis. Once the participant had thoroughly understood all task instructions and completed the practice tasks, those in the smoking condition were instructed to disable their microphone and camera and to take 5 minutes to consume their prepared cannabis. A 5-minute timer was displayed during the cannabis intake period to alert the participant when the time was up. Post-cannabis consumption, each participant was required to complete a Post-Cannabis-Use Survey[28], which took less than 5 minutes to complete. All participants would then proceed to the experimental session after logging off from the video platform. This protocol was established so that participants would not perceive any observational presence, thereby facilitating the completion of the task within an uninhibited and naturalistic environment.

Think Aloud Paradigm (TAP)

The data used in this study were entirely derived from the TAP task, adapted from the model established by Raffaelli[2]. The TAP was a 12-minute block during which participants were asked to verbalize their conscious experiences in the absence of any prompts. A fixation cross was displayed throughout the 12 minutes. Following this 12-minute block, participants were prompted with three questions, however, the responses recorded from these questions were not factored into the subsequent analysis.

Analysis

Data Transcription

The TAP task audio recordings were downloaded from Pavlovia and transcribed utilizing the medium English Whisper model from OpenAI[29]. Given the study's inherent time constraints, manually transcribing the recorded audio data was deemed impractical. The medium Whisper model has been demonstrated to surpass most other transcription tools currently available in the market[30]. Although the transcriptions were not manually reviewed for accuracy, OpenAI assures a high level of transcription fidelity with the Whisper transcription tool. Additionally, the medium model has been shown to have a minimal word error rate when transcribing English speech even with pronounced accents[30]. Therefore, for the purpose of this study, we confidently rely on the transcripts produced while noting the limitations of this tool.

Data Preprocessing

The acquired transcription data was preprocessed according to the methodology outlined by Christensen[31], along with a few modifications based on the specific requirements of this study. First, all the characters in the transcribed data were converted to lowercase. This standardized the text data and ensured that identical words with varied capitalization (for instance, "Dog" and "dog") are recognized as repeating rather than contrasting individual units. Following this, the data was prepared for the process of tokenization by removing punctuations, numbers, and dates. The tokenization step involved the segmentation of the text data into individual units called tokens. For this study, a single unit or token is defined as an individual word. Once a list of tokens was extracted from the data, it was parsed to remove common English stop words and fillers (list of English stop words in the NLTK package, along with the following fillers: 'like', 'um', 'uh', 'er', 'ah', 'yeah', 'na', 'im', 'oh', 'hmm'). . This is followed by lemmatization, a process of reducing words to their root forms. For instance, the tokens "good" and "great" are reduced to "good", and "go" and "going" are represented as "go". Once the transcribed data has gone through this sequence of preprocessing steps, it is deemed clean and suitable for estimating a semantic network.

Cooccurrence Semantic Network Estimation

A cooccurrence network estimation method was used to construct separate semantic networks for each of the participant's sessions. In this approach, nodes in the network represent unique words (tokens), while edges signify the cooccurrence of two words within a specific window size. The choice of window size is pivotal, as it influences the structure of the resultant semantic network. Different window sizes help capture the structural or small temporal relationships between words which could be useful when using small data sets. This study has chosen to use a larger window size of 10 to help capture more pragmatic relationships between words over a larger time scale[32–35]. To estimate a semantic network, the number of unique tokens is first calculated. Following this, a cooccurrence matrix of NxN, where N is the number of nodes, is used to store the word cooccurring frequencies. If a word cooccurs with another word multiple times throughout the data set, the corresponding frequency in the matrix is increased. Cooccurrence frequency was weighted by the inverse of the distance between the cooccurring words. This aids in representing a strong relationship between words in the data set that are closer to each other. Finally, the NetworkX library in Python is used to convert the cooccurrence matrix into an undirected, labelled graph with nodes that represent words and edges with weights that represent co-occurrence strength[36].

Network Measures

Network measures were then calculated based on the resultant networks. The network measures used in this analysis are as follows: Number of nodes, number of edges, mean degree centrality (the average number of edges per node in the network), mean betweenness centrality (measures the average number of shortest paths passing through each node), mean clustering coefficient (measure of the degree to which nodes in a network cluster or group together), average path length (average shortest paths between all pairs of nodes), modularity (measures the strength of division of a network into groups) and number of communities (number of groups or clusters in a network) using the Louvain algorithm for community detection[37].

Statistical Analysis

The experimental design implemented in this study results in different grouping conditions. Since each participant is administered two sessions, each session would belong to one of two paired groups: One group containing all participants' smoking sessions (smoking group) and another for the sober sessions (sober group). The random assignment of task order divides participants into two independent groups: one group containing all the participants that started their sessions with the TAP task (TAP group) and another group with all the participants that started both sessions with the FAST and TRT tasks (FAST group). Furthermore, randomly assigning a smoking session for each participant generates two independent groups: One group with participants assigned to smoke in their first session (session-1 group) and another with participants assigned to smoke in their second session (session-2 group). The 4 independent groups resulting from random assignments can each be divided further into two paired groups. The independent groups can further be subdivided into smoking and non-smoking groups since each participant in any of these groups contains two entries, one from the smoking session and another from the sober session. All grouping conditions were considered in the statistical analyses of the acquired data. Two-tailed non-parametric testing was used to analyze this data set due to the small sample size and the lack of normality and consistent variance within the data. To correct for multiple comparisons, the Bonferroni-Holm correction method was applied to all reported p-values with an alpha value of 0.05. The Mann-Whitney U Test was applied to compare independent measures investigating the general effect of cannabis (smoking vs. sober), as well as task order and session effects (TAP vs. FAST, and session-1 vs. session-2). Additionally, the Wilcoxon Signed Rank Test was used to analyze differences between dependent groups within the conditions (i.e., TAP smoking vs. TAP sober). Additionally, the network measures data was normalized using the min-max normalization method to generate easily readable plots.

Results

Estimated Semantic Networks

Estimated networks from the think aloud data of a participant's smoking and sober sessions can be seen in Figures 1 and 2, respectively.

Smoking Vs. Sober

On average participants produced fewer words during their smoking session (mean 1107.84, SD = 506.59) compared to their sober session (mean=1313.46, SD = 495.42; p-value = 0.017, effect size = 0.79). Of these words, there were slightly fewer unique in meaning as measured by the number of nodes, in the smoking condition (mean = 261.62, SD = 94.24) compared to the sober session (mean=291.70, SD = 82.94; p-value = 0.041, effect size = 0.77). Similarly, there were fewer edges in the smoking condition (mean =3554.51, SD = 1497.67) compared to the sober session (mean=4097.51, SD = 1388.49; p-value = 0.023, effect size = 0.78). Despite the difference in number of nodes and edges, there was no significant difference in the number of clusters within the networks (Nsmoke = 8.95, Nsober = 9.16; p-value = 1). There were no significant differences in the average degree centrality, average clustering coefficient, average path length, and modularity. However, the average betweenness centrality of the nodes in the smoking session (mean =0.0070, SD = 0.0031) was significantly larger than in the sober session (mean=0.0062, SD = 0.0025; p-value = 0.029, effect size = 0.77), indicating that the clusters tended to be less distributed and nodes of one cluster were connected to other clusters more regularly (see Figure 3, and Table 1).

Comparing session 1 vs session 2 network measures within the group of participants assigned to smoke during session 1

Results show significant differences in the number of nodes, number edges, word count, degree centrality, and betweenness centrality between the smoking and the sober conditions within the group of participants that were assigned to smoke during session 1. The average word count in the smoking session (mean=1119.6, SD=494.7) was significantly lower than the average word count in the sober session (mean=1431, SD=362.0, p-value = 0.012, effect size = 0.88). The average number of nodes in the smoking session (mean=268.75, SD = 87.11) was significantly lower than the average number of nodes in the sober session (mean=309.45, SD=362.0, p-value=0.033, effect size=0.87). The average number of edges in the smoking session (mean=3604.65, SD = 1377.03) was significantly lower than the average number of edges in the sober session which was (mean=4407, SD=1082.098, p-value=0.0092, effect size=0.895). The average degree centrality in the smoking session (mean=10.88, SD=1.64) was significantly lower than the average degree centrality in the sober session (mean=11.99, SD=1.64, p-value=0.022, effect size=0.86). The average betweenness centrality in the smoking session (mean=0.0067, SD = 0.0024) was significantly higher than the average betweenness centrality in the sober session (mean=0.0054, SD=0.00097, p-value=0.011, effect size=0.89). There were no significant differences between conditions in the average path length, average clustering coefficient, modularity, and number of communities (see Figure 4, and Table 2).

Session-2, TAP, and Fast Groups Statistical Test Results

Session 1 and session 2 network measures within the group of participants assigned to smoke during session 2 were compared using the Mann-Whitney U Test. Results showed no significant differences between the smoking and the sober conditions network measures (see Figure 5, and Table 2). To assess the potential effects of randomly assigning the smoking session, the Mann-Whitney U Test was used to compare session 1 sober vs. session 2 sober network measures and session 1 smoking vs. session 2 smoking network measures. Results from both tests showed no significant differences in network measures indicating no difference in smoking during session 1 or session 2. Furthermore, starting with either TAP or FAST does not seem to influence the effects of cannabis on thought patterns, as the non-parametric test results show no significant differences (see Table 3). Within each group (TAP and FAST), the smoking and sober network measures were analyzed using the Wilcoxon Signed Rank Test, and between these groups, TAP sober vs FAST sober and TAP smoking vs FAST smoking were compared using the Mann-Whitney

U Test (complete data can be found in supplementary material).

Discussion

The present study employed the TAP task to capture thoughts at rest and used network science approaches to quantify the structure of thought dynamics and explore its variability under the influence of cannabis. When comparing each participant's smoking session with their sober session, results suggest that there was a significantly lower word count, number of nodes, number of edges, and significantly higher betweenness centrality in the smoking condition, as seen in Figure 3. The word count represents the total number of words generated during each 12-minute TAP block. The number of words used in each session are as expected if participants completed the task as instructed. English speakers produce approximately 6 syllables per second while speaking, and there is on average 1.35 syllables in a typical spoken word[38–40]. This would mean that 12 minutes of uninterrupted speech would have a word count of 3196.8. However, given the nature of the TAP task and that human speech usually includes long pauses between thoughts, a lower word count is justified. A higher word count during the sober sessions may indicate more verbosity when participants were not under the influence of cannabis. The significantly fewer number of nodes in the smoking condition adds to this observation while also suggesting lesser diversity in thoughts. However, this significant difference in word count and the number of nodes could also be due to the influence of cannabis on the participants' ability to verbalize their thoughts consistently[41].

The results also indicate that the number of edges in the smoking condition are significantly fewer than in the sober condition. Since edges represent word cooccurrences, fewer edges in the smoking condition could suggest that the range of connections or transitions between themes is more limited when the participant is under the influence of cannabis. However, due to the nature of the network estimation approach chosen in this study, this significant difference might simply depict the participants' reduced vocabulary under the influence of cannabis (i.e., participants are using the same words multiple times, reducing the number of edges being drawn between nodes). Betweenness centrality measures the number of shortest paths that pass through a node. Therefore, the significantly higher betweenness centrality in the smoking session could suggest the presence of more words that serve as "bridges" that connect to many other words throughout the session. This would suggest that certain words are more central to the overall thought process when under the influence of cannabis. In essence, although the range of ideas in the smoking condition is rather narrow, some themes appear disproportionately influential to other themes.

The same trend in significant differences in network measures was seen when comparing the smoking and sober conditions within the group of participants that smoked cannabis during session 1 (Figure 4). Results showed significantly lower word count, number of nodes, number of edges, and significantly higher betweenness centrality in the smoking condition. Along with this, results showed significantly lower degree centrality in the smoking condition than in the sober condition. Degree centrality is the number of edges a node has. This measure could suggest that participants, when sober, tend to use the same cooccurring word pairs more frequently.

However, no significant differences in network measures were observed between the two conditions among the group of participants that were assigned to smoke cannabis during session 2 (Figure 5). This could imply some form of priming or anticipation effect in the participants or there might be other factors related to the temporal experience of the sessions, or the effects of cannabis on learning that might influence the results[42].

The results also show no significant difference in starting both sessions with the TAP task versus ending the session with the TAP task. This result is not as expected as the level of cannabis intoxication varies over time, and hence, it could be expected that the effects on thought dynamics would also vary over time[12]. It is possible that the small sample size is not sufficient to identify this temporal effect.

Despite the vast amount of data collected in this study and the significant difference seen between the smoking and sober conditions, it is not possible to definitively claim that cannabis influences thought dynamics or that it appears to decrease the variability in thought patterns. This is due to the small sample size, as well as the number of confounding variables within the experimental design (task order, assigned smoking session, cannabis strain and THC concentration, and other environmental variables). With a larger sample size, the analysis will hold more statistical power allowing for more definitive claims. However, these findings still provide a fascinating starting point to study thought dynamics and cannabis as they appear to point towards the idea that cannabis may have an influence on the quantity and the structural organization of thoughts. The unique finding about the order of sessions also indicates potential areas for deeper exploration, and consulting the questions answered during each session could provide more information to explain the differences seen in the data.

In conclusion, the findings from this study do not have sufficient statistical power to claim that cannabis has an influence on thought dynamics, due to the limitations posed by the experimental design of the study and the small sample size. However, this study is still ongoing, and more participants are being recruited for data collection. Some avenues for future research would include having participants only complete the TAP task and to have the 2 sessions spaced out over a longer period to eliminate other factors that might be influencing the results. The algorithm used for network estimation could be improved by combining it with pre-trained language models like BERT to include the semantic meaning of the thought content. Finally, future studies should employ manual verification for transcription accuracy to improve the confidence in the observed data.

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Additional information

Supplementary material (all research data) is available in this OneDrive folder, and the relevant code is accessible in the StonedOutLoud GitHub repository.

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Measure	Smoking				Sober				Test	
	μ	M	σ	IQR	μ	M	σ	IQR	p	EF
Nodes	261.6	261.0	94.2	111.0	291.7	282.0	94.2	93	0.04	0.77
Edges	3554.5	3662	1497.7	1773	4097.5	3876	1388.5	1644	0.02	0.78
Degree Centrality	11.0	11.0	1.7	2.2	11.6	11.6	2.1	2.2	0.11	0.71
Betweenness centrality	0.0070	0.0006	10.0031	0.0023	0.0062	0.0055	0.0025	0.0016	0.29	0.77
Clustering Coefficient	0.034	0.034	0.017	0.021	0.031	0.029	0.015	0.015	1.0	0.56
Average Path Length	0.32	0.32	0.016	0.018	0.32	0.32	0.021	0.016	1.0	0.62
Modularity	0.46	0.47	0.059	0.060	0.46	0.45	0.069	0.066	1.0	0.53
Communities	8.9	9.0	1.6	2.0	9.2	9.0	1.7	2.0	1.0	0.62
Word Count	1107	1232	506.6	612	1313.5	1286	495.4	596	0.017	0.79

Table 1. Descriptive statistics and statistical test results across the smoking and sober conditions Mean (μ), Median (M), and standard deviation (σ), p-value (p), (EF) Effect Size

Measure	Session-1										Session-2									
	Smoking				Sober				Test		Smoking				Sober				Test	
	μ	M	σ	IQR	μ	M	σ	IQR	p	EF	μ	M	σ	IQR	μ	M	σ	IQR	p	EF
Nodes	268.8	260.0	87.1	104.3	270.8	281.0	101.0	132.0	0.033	0.87	253.2	296.0	104.1	135.0	309.5	296.5	61.1	78.3	1.0	0.62
Edges	3604.7	3413.0	1377.0	1602.3	3732.3	3756.0	1638.6	2566.0	0.00092	0.90	3495.5	3853.0	1669.8	2254.0	4408.0	4418.5	1082.1	1473.3	1.0	0.61
Degree Centrality	10.9	10.9	1.6	1.7	11.1	11.1	2.4	1.5	0.022	0.86	11.2	11.0	1.7	2.2	12.0	12.2	1.6	2.3	1.0	0.50
Betweenness centrality	0.0067	0.0063	0.0024	0.0022	0.0071	0.0061	0.0033	0.0041	0.011	0.89	0.0074	0.0057	0.0037	0.0038	0.0054	0.0052	0.00097	0.0013	1.0	0.64
Clustering Coefficient	0.034	0.035	0.014	0.021	0.035	0.031	0.015	0.0071	0.25	0.72	0.033	0.029	0.020	0.024	0.027	0.025	0.015	0.014	1.0	0.60
Average Path Length	0.32	0.32	0.013	0.019	0.32	0.32	0.027	0.023	0.66	0.63	0.31	0.32	0.018	0.021	0.32	0.32	0.013	0.014	0.79	0.73
Modularity	0.47	0.48	0.056	0.071	0.48	0.46	0.082	0.079	0.61	0.80	0.45	0.45	0.062	0.083	0.44	0.44	0.052	0.050	0.16	0.82
Communities	9.2	9.0	1.4	2.0	9.2	9.0	2.1	2.0	0.91	0.60	8.7	9.0	1.8	2.0	9.2	9.0	1.3	2.0	1.0	0.65
Word Count	1119.6	1100.5	494.7	642.5	1175.2	1192.0	599.2	767.0	0.012	0.88	1094.0	1244.0	535.2	683.0	1431.0	1417.5	362.0	492.3	1.0	0.65

Table 2. Descriptive statistics and statistical test results across the smoking and sober conditions for the Session-1 and Session-2 groups Mean (μ), Median (M), and standard deviation (σ), p-value (p), (EF) Effect Size

Measure	TAP										FAST									
	Smoking				Sober				Test		Smoking				Sober				Test	
	μ	M	σ	IQR	μ	M	σ	IQR	p	EF	μ	M	σ	IQR	μ	M	σ	IQR	p	EF
Nodes	241.3	227.0	100.8	134.0	270.9	261.0	87.9	106.5	0.37	0.77	283.1	270.0	84.3	82.8	313.7	311.5	73.5	61.5	0.31	0.77
Edges	3231	3067	1529	2409	3768	3553	1483	2057	0.25	0.77	3895	3711	1425	1111	4444	4419	1226	1074	0.31	0.78
Degree Centrality	10.6	10.7	1.7	2	11.4	11.4	2.5	2.7	0.12	0.82	11.5	11.7	1.5	2.5	11.7	11.7	1.5	1.8	1	0.60
Betweenness centrality	0.0079	0.00070	0.0038	0.0040	0.0068	0.0061	0.0031	0.0023	0.29	0.76	0.0061	0.006	0.0018	0.0013	0.0054	0.0052	0.0013	0.00079	0.31	0.78
Clustering Coefficient	0.039	0.038	0.017	0.014	0.035	0.032	0.018	0.019	1.0	0.62	0.028	0.025	0.016	0.020	0.023	0.027	0.0098	0.012	1.0	0.51
Average Path Length	0.31	0.32	0.019	0.019	0.32	0.32	0.026	0.021	1.0	0.56	0.32	0.32	0.013	0.017	0.32	0.32	0.014	0.012	1.0	0.53
Modularity	0.47	0.47	0.061	0.070	0.47	0.45	0.083	0.068	1.0	0.50	0.46	0.46	0.059	0.053	0.45	0.44	0.050	0.071	1.0	0.57
Communities	8.5	8.0	1.6	2.5	8.7	8.0	1.3	2.0	1.0	0.64	9.4	9.5	1.5	1.0	9.7	9.0	1.9	1.0	1.0	0.59
Word Count	1007	989	537.2	833.5	1253	1286	596.6	769.5	0.16	0.80	1214	1233	463.2	548.8	1377	1344	367.1	364.0	0.31	0.77

Table 3. Descriptive statistics and statistical test results across the smoking and sober conditions for the TAP and FAST groups Mean (μ),Median (M), and standard deviation (σ), p-value (p), (EF) Effect Size

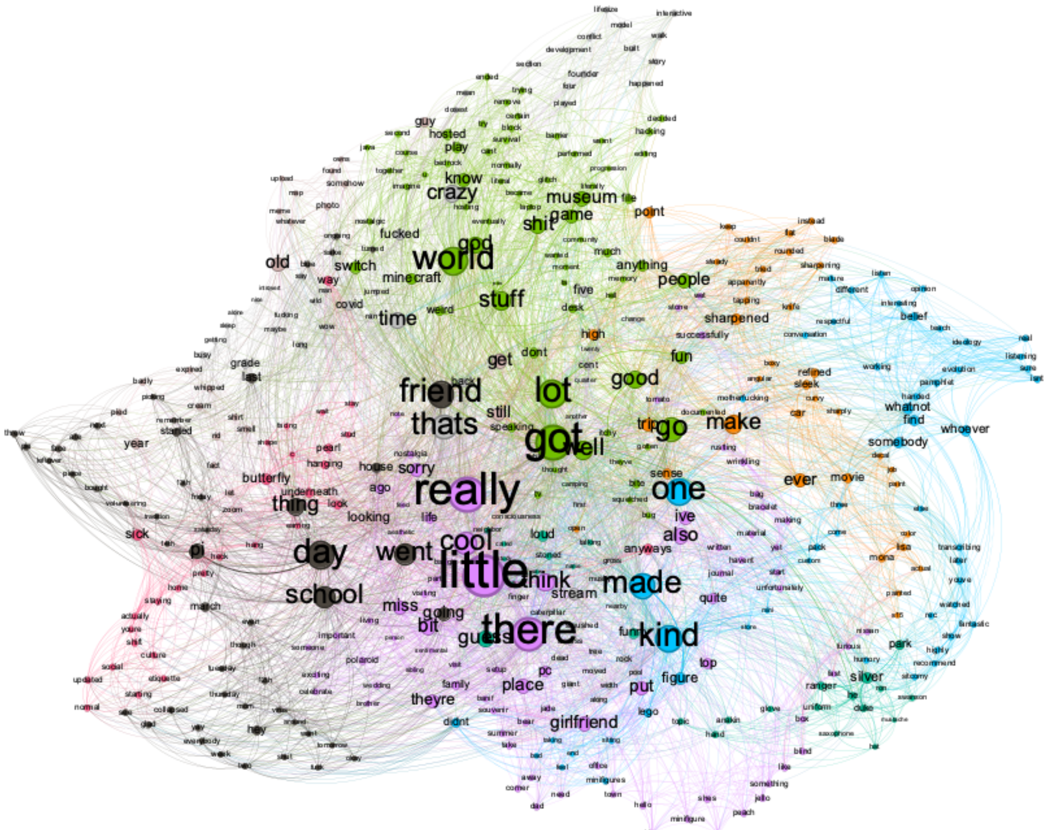

Figure 1. Cooccurrence network based on a participant's smoking session, The colored circles and lines represent nodes and edges, respectively. Larger nodes indicate a higher degree centrality (i.e., number of edges). Each color represents a community clustered by the Louvian algorithm

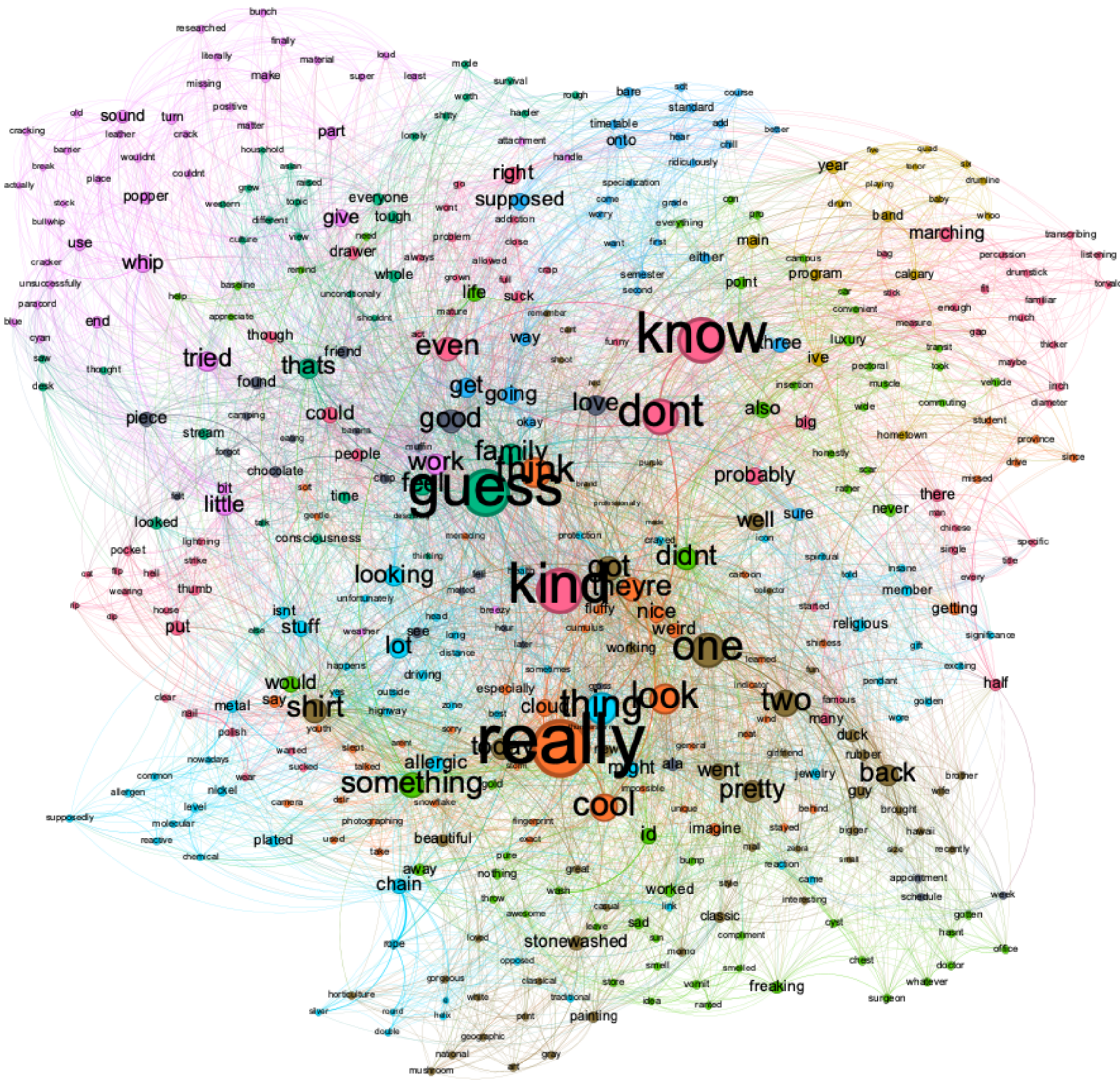

Figure 2. Cooccurrence network based on a participant's sober session, The colored circles and lines represent nodes and edges, respectively. Larger nodes indicate a higher degree centrality (i.e., number of edges). Each color represents a community clustered by the Louvian algorithm

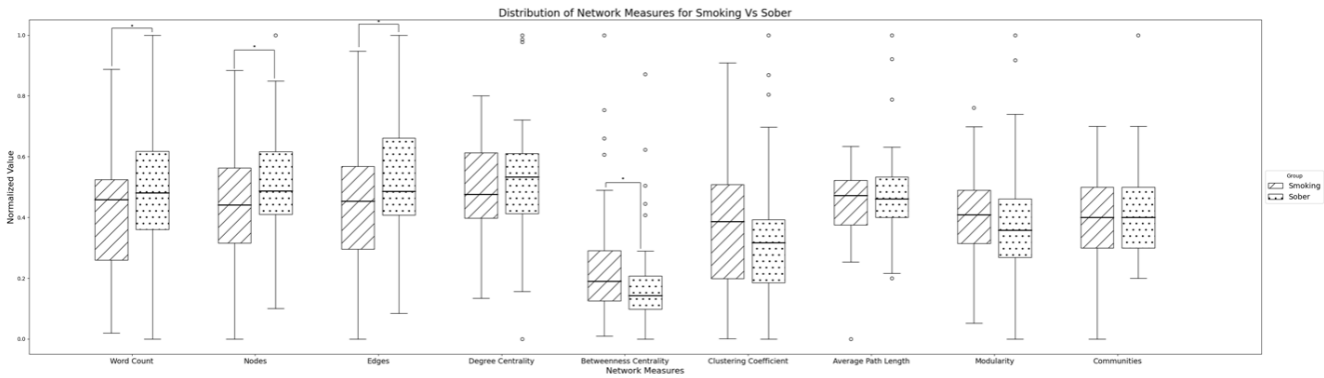

Figure 3. Box plots representing the distribution of network measures from the smoking and sober sessions across all participants irrespective of assigned smoking session and task order.

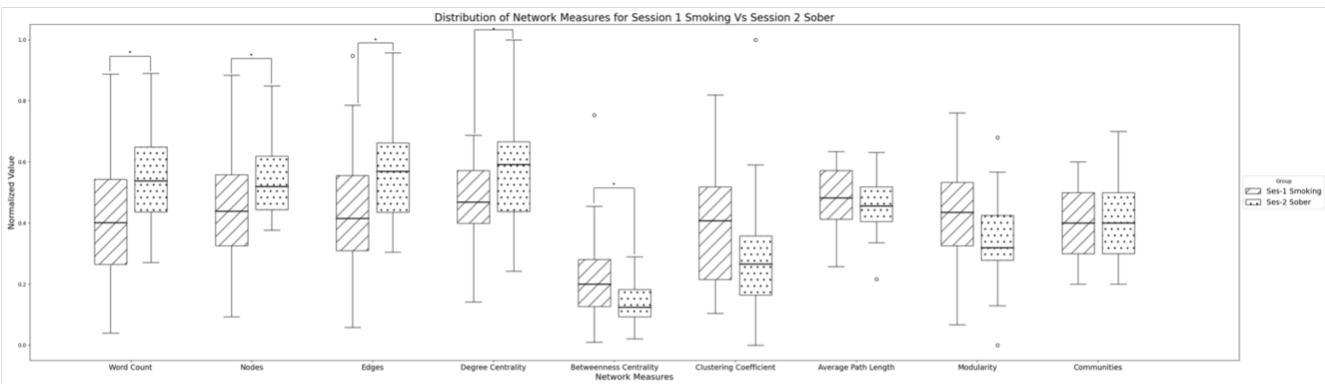

Figure 4. Box plots representing the distribution of network measures from the smoking and sober sessions for the group of participants assigned to smoke during session 1 irrespective of task order.

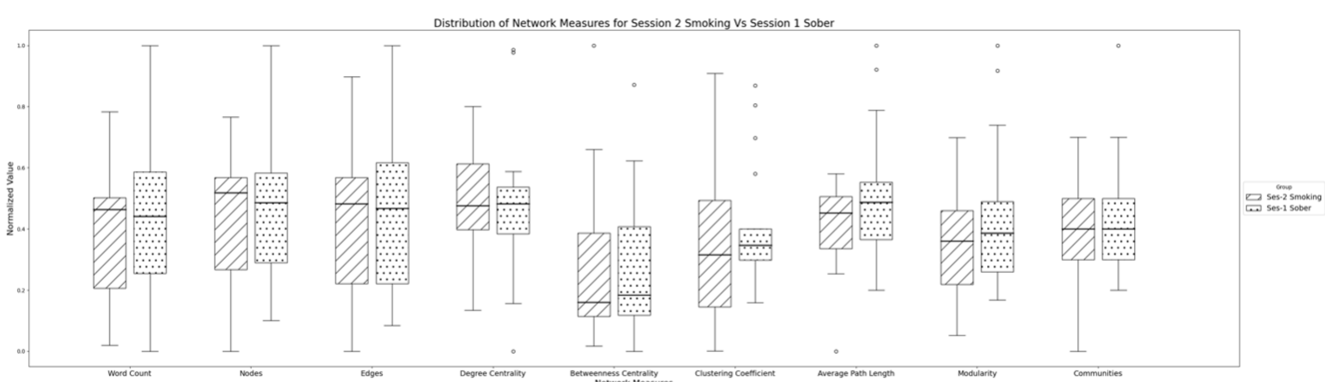

Figure 5. Box plots representing the distribution of network measures from the smoking and sober sessions for the group of participants assigned to smoke during session 2 irrespective of task order.