Towards Comprehensive Language Analysis for Clinically Enriched Spontaneous Dialogue

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ABSTRACT

Contemporary NLP has rapidly progressed from feature-based classification to fine-tuning and prompt-based techniques leveraging large language models. Many of these techniques remain understudied in real-world, clinically enriched spontaneous dialogue. We fill this gap by systematically testing the efficacy and performance of varied NLP techniques on transcribed speech collected from patients with bipolar disorder, schizophrenia, and healthy controls taking a focused, clinically-validated language test. We observe impressive utility of feature-based and language modeling techniques, finding that these approaches may provide a plethora of information capable of upholding clinical truths about these subjects. Building upon this, we establish pathways for future research directions in automated detection and understanding of psychiatric conditions.

1. Introduction

The use of NLP to support mental healthcare has gained prominence recently with research focusing on a variety of conditions including schizophrenia (Kalbitzer et al., 2014; Krishna et al., 2012), mood disorders (Lin et al., 2016; Pantic et al., 2012), personality disorders (Rosen et al., 2013), eating disorders (Mabe et al., 2014) and others (Turcan and McKeown, 2019a; Tadesse et al., 2019; Zirikly et al., 2019a; Morales et al., 2018). The promising capabilities of these approaches have been demonstrated using a range of techniques—for instance, Singhal et al. (2022) showed that LLMs with sizes up to 540B parameters can encode clinical and medical knowledge. Most NLP work towards mental health support has thus far focused on social media (e.g., Twitter (Kang et al., 2016) or Reddit (Yan et al., 2019)) rather than clinically-enriched data, extracting and annotating user data based on social features deemed relevant by technical researchers but not necessarily validated by clinicians. Consequently, the question of whether these reported NLP techniques hold relevance for clinical data still requires thorough investigation. In this paper, we comprehensively and empirically investigate this question using a clinically enriched dataset drawn from actual patient dialogues and their performance on standardized clinical tests.

Our dataset includes patient-psychologist conversations between 644 participants categorized based on their status as healthy control (HC) participants or participants with schizophrenia (SZ) or bipolar disorder (BD). Each participant engaged in a focused test during which they conversed for approximately four minutes across two scenarios. A previous paper introducing this dataset (Aich et al., 2022) established a feature-based performance benchmark, but did not provide details about feature importance or participant demographic trends, nor did it apply more contemporary LLM-based models to the task. Our contributions are:

- We systematically and comprehensively analyze these features and their significance across age and gender demographics.
- We assess feature-based statistical significance and importance when differentiating be-

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tween feature groups.

- We use an encoder-based topic model to extract relevant topics from participant dialogue to visualize and confirm clinical observations.
- We show that large language model (LLM) settings can find patterns in subject dialogue.

Taken holistically, our work demonstrates how a range of more traditional and recent NLP methods can be leveraged to understand and work with clinically enriched spontaneous dialogue.

2. Data

We collected our data by audiorecording 644 participants as they took a standardized clinical test known as the social skills performance assessment (SSPA) (Patterson et al., 2001b). The SSPA is a conversational test designed to delineate social skills across multiple dimensions. Our participants were recruited based on their confirmed diagnoses of specific clinical conditions and medical histories, with the exception of those categorized as healthy controls (Aich et al., 2022). Participants were thus grouped into three categories: people with schizophrenia (referred to as SZ hereon; n=247), people with bipolar disorder (BD; n=286), and healthy controls (HC; n=110).

The SSPA has proven to be a useful and bias-free assessment and a strong predictor of social performance, and it has served as the basis of clinical rehabilitation-based work (Leifker et al., 2010; Miller et al., 2021). It includes two improvisational scenes, each of which involve a participant conversing with an interviewer (a trained psychologist). The scenes probe for specific but different information. The conversations were audiorecorded and later transcribed, and the transcribed dialogues were annotated by clinical professionals across different social skills dimensions corresponding to content relayed in the conversation.

The first scene seeks to facilitate a *friendly* interaction, to assess the social appropriateness with which the participants introduce themselves and engage in conversation. The participant is asked to imagine that they have just moved into a new neighborhood and must introduce themselves to a new neighbor. The second scene seeks to facilitate a *confrontational* interaction. Participants are given a focused, defined objective: They are told to imagine that they have a leaky pipe in their apartment which has not been fixed for a while, and they need to complain to their landlord and get it fixed. Dual annotation by clinical professionals across the SSPA skills dimensions achieved strong ($\kappa > 0.8$) inter-annotator agreement scores.

In our earlier work (Aich et al., 2022), we established dataset validity using a binary classification benchmark to discriminate between pairs of subject groups. The classifier was trained using 138 extracted linguistic features. We only ran experiments using half of the data (n=300 subjects), and since our focus was on data validation and establishing proof of concept, we did not study individual feature importance or significance. Here, we perform a more thorough set of experiments across the full SSPA dataset to deepen our insights regarding this task. We incorporate metadata pertaining to age and gender demographics, and experiment with LLM-based methods to demonstrate the ability of contemporary NLP approaches to reveal clinical patterns in a rich dataset.

Group A	**Group B**
Positive Score	Personal pronouns
Preposition	Authentic
Drive	Diction
Achieve	Linguistic
Cognition	Function
Cause	i-pron
Discrepancy	Friend
Non Fluency	Quantity
Filler Words	Certitude
All Punctuations	Sad Emotion
	Death
	Moral
	Adjectives

Table 1: Features showing statistically significant differences between age groups, indicating the group with higher feature values.

3. Analysis of Linguistic Differences Between Participants

We sought to discern and differentiate the linguistic patterns among participants across *Age*, *Gender*, and *Diagnoses*. To do so, we extracted our original 138 linguistic features (Aich et al., 2022) and studied their group-level differences. Briefly, these features include temporal, sentiment, psycholinguistic, lexical, and emotional characteristics. Examples of specific features within these groups include the recorded time taken to complete a task or utterance, the overall sentiment of a conversation, features derived from specific lexicons or tools such as the Linguistic Inquiry and Word Count (Boyd et al., 2022a, LIWC), and various measures of lexical diversity (Mass, 1972).

3.1. Age

For age-based analysis, we grouped participants into two categories depending on whether they were greater than or equal to 50 years old: Group

Female	Male
Numbers	Universal Quantifiers
Negative Tone	Insight
Positive Tone	Discrepancy
Swear Words	Focus Present
Time	Focus Future
Social Behavior	Netspeak
Conflict	Non Fluency
Exclamation	Punctuation
TTR	Maas Lexical Diversity
Summer	Female
Anticipation	Male
Conjunctions	
Herdan	
Dugast	

Table 2: Features showing statistically significant differences between gender groups, indicating the group with higher feature values.

A (age < 50) and Group B (age ≥ 50).[1] We computed standardized t-tests to find features with significantly different values between the two groups, allowing us to determine the association between linguistic traits and age and more fully understand how this demographic dimension may influence predictive models trained on the SSPA data. In Table 1, we highlight features that were found to have significantly different values between groups, indicating the group for which the feature value was higher. We observe that participants in Group A used more cognition-related words than those in Group B, aligning with Koch et al. (2022) which demonstrates a negative correlation between age and causation.

3.2. Gender

For gender-based analyses, we divided participants into two groups: male and female.[2] We tested feature correlation with both genders, and features with the highest correlation were compared using t-tests to assess group-level statistical significance. We show the dominant groups for statistically significant features in Table 2. We observe that males used more universal quantifiers (e.g., "all" or "nothing" words), present tense and future tense words, exclamations, and anticipatory speech. We observed that females had higher insight scores, discrepancy in speech, and sentiment and affect in speech. These findings support clinical observations such as that of Fast and Horvitz (2016), which shows that women verbalize more cognition and can more easily characterize non-dogmatic language.

3.3. Diagnoses

To analyze features across diagnostic groups (*BD*, *SZ* and *HC*), we first computed mean values for each feature, for each group, and then extracted features that exhibited statistically significant differences between their group-based means. We elaborate on this process below.

3.3.1. Determining Feature Significance

We extracted 138 linguistic attributes from the SSPA dataset, all of which were represented as normally distributed continuous values. Ross and Willson (2017) suggest that having a sample size greater than or equal to 30 decreases the chance of making a Type 2 error, and in our case each diagnostic group had > 30 samples. Each of the three groups was also independent of the others, thus satisfying all assumptions for the analysis of variance (ANOVA) test (Parab and Bhalerao, 2010). We perform one-way ANOVA tests to analyze the differences between groups of participants with different mental health diagnoses.

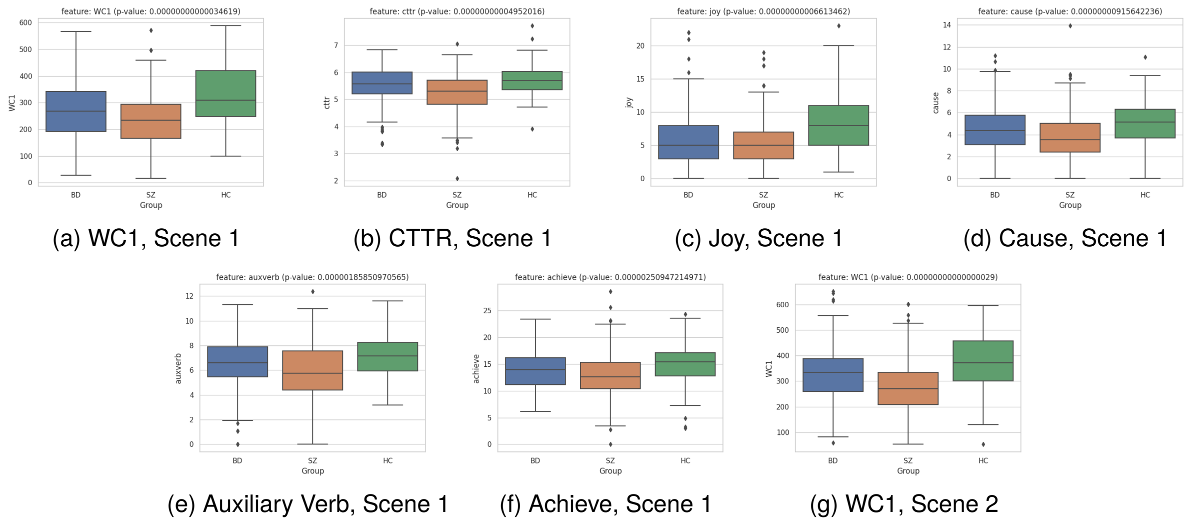
In ANOVA, a large F-value suggests that the group means are more spread out, indicating that at least one group might be significantly different from the others; conversely, with small F-values the data points within each group are more dispersed, making it harder to detect significant differences. The ANOVA test derives a p-value by comparing the resulting F-value with the F-distribution using the appropriate degrees of freedom (Bewick et al., 2004). If the p-value is less than a specified threshold (typically < 0.05), the null hypothesis is rejected, suggesting a statistically significant difference between at least one pair of the group means. We used the `statsmodels` module in Python to implement the ANOVA test.

3.3.2. Differentiating Diagnostic Groups

While one-way ANOVA identifies whether there are any significant differences among the group means, it does not specify which groups differ from each other. To pinpoint the groups with differing means, we conducted a post-hoc Tukey's HSD (Honestly Significant Difference) on the significant features since it shares the same assumptions as ANOVA. Tukey's HSD evaluates all possible

[1] This division reflects that used to originally define elderly SSPA participants (Patterson et al., 2001a).

[2] Participants may hold diverse gender identities. We asked participants to self-report their own gender, and all except one reported their gender as *Male* or *Female*. The remaining participant wrote "3," and we excluded this participant's data from analyses reported in this subsection since a single data point is an insufficient basis from which to draw conclusion.



(a) WC1, Scene 1 (b) CTTR, Scene 1 (c) Joy, Scene 1 (d) Cause, Scene 1

(e) Auxiliary Verb, Scene 1 (f) Achieve, Scene 1 (g) WC1, Scene 2

Figure 1: Distribution of features across diagnostic groups.

pairs of group means, determining which specific groups' means differ significantly (Glen, 2016).

3.3.3. Feature-Related Hypotheses

Several studies have investigated linguistic features for diagnosis of schizophrenia and bipolar disorder, giving rise to our hypotheses as follows:

- **H1:** Voleti et al. (2019) identified language features related to the SSPA that could successfully distinguish members of a clinical group that participated in the task (AUC=0.96), and also between subjects within the clinical group with SZ and BD (AUC=0.83). This motivates our hypothesis that further investigation into linguistic features could help uncover underlying characteristics of SZ and BD.
- **H2:** Park et al. (2018) examined lexical diversity of six active communities on Reddit. Three were related to mental health, including SZ and BD (r/depression, r/schizophrenia, r/bipolar), while the others were selected as controls and focused on unrelated topics (r/happy, r/loseit, r/bodybuilding). They found that members of r/bipolar and r/schizophrenia communities obtained poorer lexical diversity scores compared to the other communities, but they did not observe a significant difference between r/bipolar and r/schizophrenia. We hypothesized that lexical diversity of the BD and SZ groups could be better characterized and differentiated through an analysis of corrected type-token ratios (CTTR). CTTR offers a standardized measure of lexical diversity that is less influenced by the overall text length, achieved through the application of the square root of twice the number of tokens (Torruella and Capsada, 2013).
- **H3:** Chrobak et al. (2022) performed verbal fluency tests (VFT) on BD, SZ and HC groups, and analysis of Semantic VFT revealed that the SZ group showed lower word count than the HC group. Similarly, we hypothesized that the SZ group uses fewer words compared to other groups during both scenes.
- **H4:** Deng et al. (2018) observed that both the BD and SZ groups scored lower than HC in cognitive tests of verbal comprehension, executive functioning, and working memory, with SZ performing worst. Accordingly, we hypothesized that individuals in the BD and SZ groups would face challenges in causal reasoning, especially in Scene 2 when they confront the landlord.

Together, these studies motivate our feature comparison and highlight an advantage of using NLP for this purpose: although observational evidence may suggest an important conclusion, computationally extracting features representing this phenomenon and studying them at scale allows researchers to empirically ground these findings.

3.3.4. Results and Inferences

After conducting ANOVA and Tukey tests, we investigated feature significance across all pairs of the *BD*, *SZ* and *HC* groups to accept or reject our hypotheses. We also visualized the score distributions for each feature within each group, facilitating conclusions about language usage patterns within those groups. Table 3 describes features found to be significantly different across all groups, and Figures 1a-1g depict distributions of the corresponding features using box plots. Extra ANOVA details are in Table 4

Feature	Description	Category	Source	Scene
WC	Total word count	Psycholinguistic	Boyd et al. (2022b)	1, 2
cttr	Corrected type-token ratio	Lexical Diversity	Carroll (1964)	1
joy	Words associated with the emotion '*joy*'	Emotion	Mohammad and Turney (2013b)	1
cause	Causal words signifying a cause-and-effect relationship	Psycholinguistic	Boyd et al. (2022b)	1
auxverb	Number of auxiliary verbs	Psycholinguistic	Boyd et al. (2022b)	1
achieve	Words that reflect accomplishment	Psycholinguistic	Boyd et al. (2022b)	1

Table 3: Details of features that are significantly different across all the diagnostic groups.

Six features differentiated all three diagnostic pairs (BD vs. HC, BD vs. SZ and HC vs. SZ) for Scene 1 , and only one feature distinguished these pairs for Scene 2. When examining the feature score distributions, we observed that:

- *HC* exhibited a more diverse vocabulary in their speech compared to both *BD* and *SZ*. Among *BD* and *SZ*, *BD* demonstrated greater lexical richness.
- *HC* used a higher word count than both *BD* and *SZ*. When comparing *BD* and *SZ*, *BD* used more words.
- *HC* expressed higher levels of joy than the other groups. Between *BD* and *SZ*, *SZ* used less words associated with joy.
- *SZ* used fewer words related to causality and reasoning compared to both *BD* and *HC*. Within *BD* and *HC*, *HC* used causal words more frequently.
- *HC* used more auxiliary verbs than *BD*, and *BD* used more auxiliary verbs than *SZ*.
- *HC* displayed a higher sense of achievement in their language. Among *BD* and *SZ*, *SZ* used fewer words related to success and achievement.

Table 5 summarizes the diagnostic feature analyses across both scenes. Statistical tests identified a larger number of significant features in Scene 1 than Scene 2. Six Scene 1 features showed differences across all group pairs, whereas only one feature (WC.1) was significantly different across all pairs in Scene 2. Despite this, a similar number of features discerned either one and two significant group pairs in both scenes, and differentiating between *BD* and *HC* always proved more challenging than distinguishing *SZ*. Weiner et al. (2019) suggests that the link between mood states and linguistic capabilities in BD is intricate, with certain BD phases exhibiting linguistic traits akin to HC. Consequently, BD individuals not in acute mood episodes may retain similar linguistic functions to HC, leading to comparable language patterns. Notably, in Scene 2, the linguistic behavior of *SZ* deviated significantly from that of either *BD* or *HC* in over 90% of the significant features.

Feature	F	df	p
Achieve	13	2	0.000003
Auxverb	3.02	2	0.004
Anticipation	18.4	2	1.15e-08
All punctuation	6.18	2	0.0002
Big Words	3.95	2	0.001
Cause	19.0	2	9e-09
Drives	6.56	2	0.0001
Joy	24	2	6.1e-11
Max time	11.8	2	0.000009
Surprise	7.5	2	0.00002
Trust	16.4	2	1e-7
WPS	6.3	2	0.001

Table 4: More Features from ANOVA

4. Impact of Clinical Features

With the rise in use cases for LLMs, we also perform experiments showcasing their use with our clinically enriched data. We conduct topic modeling experiments using an encoder-only BERT model (Devlin et al., 2018), BERTopic (Grootendorst, 2022), and an encoder-decoder based Flan Unifying Language Learning (`flan-ul2`) 20B-parameter model (Tay et al., 2023).

4.1. Topic Modeling

We selected BERTopic as the backbone for our topic modeling experiments. BERTopic (Grootendorst, 2022) uses five independent sub-models to generate topic representations, giving the user flexibility to modify sub-models according to their requirements. To create topics from SSPA transcripts, we first separated the transcripts based on all possible group $\times$ scene combinations (HC

	Scene 1	Scene 2
Total features	144	144
Significant features (p<0.05)	**61**	52
Features that differentiate no pairs	2	2
Features that differentiate 1 pair	**28**	24
(BD vs. HC)	**2**	1
(BD vs. SZ)	15	15
(HC vs. SZ)	**11**	8
Features that differentiate 2 pairs	25	25
(BD vs. HC, BD vs. SZ)	**2**	1
(BD vs. SZ, HC vs. SZ)	11	**24**
(BD vs. HC, HC vs. SZ)	**12**	0
Features that differentiate all 3 pairs	**6**	1

Table 5: Comparative analysis of diagnostic features between scene 1 and scene 2.

Scene 1 (SC1), HC Scene 2 (SC2), BD SC1, BD SC2, SZ SC1, and SZ SC2). For each transcript, we extracted patient utterances using regular expressions and combined these utterances in lists to create patient dialogue subsets.

4.1.1. Building Topic Models

After constructing the subsets, we converted utterances to numerical representations (embeddings) using the SentenceTransformers (Reimers and Gurevych, 2019) framework as it is optimized for semantic similarity at the document (in our case, utterance) level. We specifically used the `all-mpnet-base-v2` model available on the HuggingFace model hub. Next, we performed dimensionality reduction on the document embeddings using UMAP (McInnes et al., 2018), a technique that retains both local and global features of the dataset while reducing its dimensions.

With our dimensionality-reduced document embeddings, we used HDBSCAN (McInnes et al., 2017) to cluster our data. We selected HDBSCAN based on its capability to detect clusters of varying shapes and outliers when applicable. In our case, this ensures that utterances from the same transcript are not compelled to be grouped within the same cluster. Given the varying degrees of density and shapes exhibited by HDBSCAN clusters, centroid-based topic representations are not necessarily anticipated; thus, to create topic representations that do not rely heavily on cluster structure assumptions, we employed a bag-of-words approach. All words within a cluster were aggregated into a single document (Grootendorst, 2022), and from that bag-of-words representation we sought to learn what distinguished one cluster from another. We used a class-based TF-IDF (cTF-IDF) approach for this, focusing on topics rather than individual documents or words (Grootendorst, 2022). Finally, we trained our topic models based on these pipelined sub-models.

4.1.2. Experiments and Results

We interpreted generated topics using the BERTopic *visualize_topics()* and *visualize_documents()* functions. *visualize_topics()* is inspired by the LDAVis method, which represents topics in two-dimensional space using circles to represent topics and the distance between them to represent topic similarity (Sievert and Shirley, 2014). Figures 2a–2f depict topic distributions for each diagnostic group $\times$ scene.

In Scene 1, we observed that HC discussed fewer topics when introducing themselves compared to BD and SZ. Most of the less frequent topics were closely related to more common topics, forming large clusters that were distant from each other. This suggests that individuals in the HC group tend to stay focused and on-topic during their conversations. In contrast, BD and SZ exhibited a different pattern, being less direct in their communication and often diverging from the main topic. On average, the BD group discussed a greater number of topics, and the distances between these topics were larger. We can infer that BD patients tend to become more easily distracted during their conversations and convey a wider range of information compared to other groups.

In Scene 2, patients were specifically asked to confront their landlords. This task focus reduced the number of discovered topics across all groups. We observed that participants in the HC group predominantly explained their concerns to the landlord by adhering to a single topic, whereas people in the BD and SZ groups often strayed to different topics and lost focus while addressing their issues.

4.2. Theme Identification

The ability of LLMs to generalize and pick up information in context has improved rapidly (Brown et al., 2020), and this process removes the need to backpropagate and update weights like in supervised fine-tuned settings. This saves training time and allows us to leverage compute resources for direct inference. We identify topical themes by prompting an encoder-decoder architecture. The flan model which extends t5, `flan-ul2`, has been proven useful and reliable for summarization tasks (Raffel et al., 2023). This model also provides a

(a) BD Subjects, Scene 1
(b) BD Subjects, Scene 2
(c) HC Subjects, Scene 1
(d) HC Subjects, Scene 2
(e) SZ Subjects, Scene 1
(f) SZ Subjects, Scene 2

Figure 2: Topic visualizations with intertopic distance maps.

large receptive field of 2048 which makes it ideal for our zero-shot task setting.

We frame theme identification similarly to text summarization, with the inputs being the topics produced by BERTopic and the output being theme titles. We use the following prompt and provide seven phrases (topic words identified by the topic model) as demonstrated below:

```
For these given phrases identify a
theme that captures all the phrases.

Phrase 1
Phrase 2
.
.
Phrase 7
```

We then expect the model to return a theme consisting of a word or short phrase capturing the essence of the input phrases. We use `flan-ul2` with PEFT-LoRA (Mangrulkar et al., 2022) and 8-bit quantization to account for GPU limitations. Inference is run on 7 T4 GPUs. The results are shown in Table 6.

From the identified themes, we observe that for Scene 1, the HC group quickly understands the task at hand, generally referring to a *new neighborhood*. We also observe that members of the BD group appear to discuss topics that are closely related but tangential to introductions, such as their cat or landlords. For members of the SZ group we observe a clear difference from the other groups. The first theme is *Don't know what to say*, which may align with catatonic behavior observed in people with schizophrenia (Jain and Mitra, 2020).

For Scene 2, we observe a similar pattern. Members of the HC group quickly discuss *Tenant rights*, whereas members of the BD and SZ groups reach the same theme later. We observe that HC participants can consistently maintain focus as opposed to other groups, as demonstrated through both the visualizations and the identified topic themes.

5. Discussion and Conclusion

In this paper we systematically investigated the reliable and trustworthy use of NLP methods for clinically enriched data. We studied patients' ages, genders, and clinical diagnoses in concert with their transcribed speech in a clinically validated spontaneous speech task. Through a study of 138 language features, we assessed feature importance and found that certain features are more associated with certain demographic traits. We also conducted multi-faceted statistical tests to dis-

Subject + Scene	Topic	Theme
BD Scene 1	Topic 0 Topic 1 Topic 2	My Cat Landlord Welcome
HC Scene 1	Topic 0 Topic 1 Topic 2	New Neighborhood Okay I am
SZ Scene 1	Topic 0 Topic 1 Topic 2	Don't know what to say Landlord Nice to meet you
BD Scene 2	Topic 0 Topic 1 Topic 2	how long will it take Tenant Rights leak
HC Scene 2	Topic 0 Topic 1 Topic 2	Tenant Rights Okay Thank You
SZ Scene 2	Topic 0 Topic 1 Topic 2	Water Tenant Rights Leak

Table 6: FLAN-UL2 theme identification.

cover which features reliably differentiate between diagnostic groups. We also demonstrate that the original set of 144 features can be reduced to 25 without performance reduction, helping us know which features are noisy and which are relevant.

Later, we showed that unsupervised topic modeling using encoder-based LLMs reveals clinically supported patterns. For instance, we see that members of the HC group exhibit better focus and more conciseness, relation, and close clustering among discussion points as opposed to members of the BD or SZ groups, as supported by detailed visuals and analyses. Finally, we prompted the `flan-ul2` model to identify themes from conversations in each subject group. Across both scenes and all groups we observed that HC participants arrived at desired topics more quickly and remained focused on them over the long term. Members of the other groups, and especially SZ, seemed less on-target, with many participants seeming unsure of what to say or how to start a friendly scene. This was also replicated in the more confrontational Scene 2.

An overarching outcome of this study was the observation that feature engineering and language modeling approaches carry separate but complementary advantages when analyzing this data. For instance, protected data such as ours cannot be run on remote servers (e.g., those used to serve OpenAI APIs) which record data logs. However, engineering many features and then intelligently reducing that feature set to statistically significant subgroups shows us which characteristics best discriminate between groups. While some features are better for understanding demographic splits of age or gender, others are better for understanding diagnostic labels or for (importantly) upholding known clinical truths. NLP in healthcare has often been plagued by explainability issues, but we observed that modern and older methods are able to beautifully and visually showcase patterns in data that have been previously suggested in clinical studies. Even completely unsupervised approaches such as our theme identification technique show how properly used LLMs can provide us with useful insights. While we still question whether some LLM predictions can be trusted, we can trust clinically-grounded insights for which LLMs validate previously hypothesized patterns in latent spaces of rich data. We conclude by hoping this leads to future work towards informed NLP use in clinical spaces, advancing progress toward explainable and reasonable conclusions.

6. Limitations

In this paper, we studied how NLP may be leveraged to analyze clinically enriched spontaneous speech. Our participant size, although large compared to contemporary relevant studies, was limited compared to that seen in many NLP task domains. We reported results over all participants, but note that a larger sample size would enable additional conclusions; it may also lead to slightly different performance distributions.

We did not add any new features beyond those introduced in our prior work (Aich et al., 2022), and preserved the full dataset from that prior work. Due to resource constraints, we used a language model with 20B parameters for our prompting-based theme identification, although it is known that models less than 40B-65B do not always perform optimally in prompting settings. Finally, we did not use any models that required running an API on a remote server since this would violate user privacy by relaying sensitive data and phrases to a third-party source. All models were run and experiments conducted locally.

7. Ethical Considerations

This paper uses real human data from generous participants. We do not intend for this paper to be interpreted as understanding the medical complexities and nuances of lifelong psychiatric illnesses such as schizophrenia or bipolar disorder. Our findings merely show how NLP techniques can provide a new perspective to the understanding and interpretation of the effects of these illnesses.

Data is stored in secure servers on laboratory computers with multi-factor authenticated security systems. At any point, only approved entities have access to the data. This data was originally collected under an approved Institutional Review Board (IRB) protocol at the University of California San Diego, and all uses of the data in this paper are in keeping with the data use provisions of that protocol. We refer readers to Aich et al. (2022) for a detailed description of the data collection and preservation procedures.

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