Automated Lexical Analysis of Interviews with Schizophrenic Patients

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Abstract Schizophrenia is a chronic brain disorder that contributes to poor function and quality of life. We are aiming to design objective assessment tools of schizophrenia. In earlier work, we investigated non-verbal quantitative cues for this purpose. In this paper, we instead explore linguistic cues, extracted from interviews of schizophrenia patients and healthy control subjects, conducted by trained psychologists. Specifically, we analyzed the interviews of 47 schizophrenic patients and 24 healthy age-matched control subjects. We applied automated speech recognition and linguistic tools to capture the linguistic categories of emotional and psychological states. Based on those linguistic categories, we applied a binary classifier to distinguish patients from matched control subjects, leading to a classification accuracy of about 86% (by leave-one-out cross-validation); this result seems to suggest that schizophrenia patients tend to talk about different topics and use different words. We provided an in-depth discussion of the most salient lexical features, which may provide some insights into the linguistic alterations in patients.

1 Introduction

Schizophrenia is a chronic mental disorder affecting millions of people globally. Its symptoms are typically classified into three broad groups: positive (hallucinations and delusions), negative (apathy, blunting of affect, alogia), and cognitive (problems with attention, memory, and executive functions) [1]. The heterogeneous linguistic alterations associated with schizophrenia have been extensively studied since the last century [2, 3]. As words and expressions contain a wealth of information re-

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garding emotions and behavior [4, 5], linguistic analysis is becoming a common tool for research in psychiatry [6, 7]. In recent years, technological advances have made it increasingly faster and more cost-effective to collect a variety of data, a data-driven approach may lead to novel discoveries and treatments in the realm of mental health [8]. In this paper, we follow such data-driven approach.

A typical lexical based tool for analyzing language is the Linguistic Inquiry and Word Count (LIWC) [9]. The latest version, LIWC 2015 [10], provides several subsets of words representing different emotional states or characteristics. Some studies have applied LIWC to essays written by schizophrenic patients. A linguistic analysis of written self-descriptive tasks completed by schizophrenic patients and controls found no differences in the use of words related to emotions (both positive and negative) between patients and control subjects when describing themselves [11]. On the other hand, analysis of standardized written assignments by psychiatric outpatients and control subjects revealed that patients used fewer words pertaining to optimism/energy, basic cognitive mechanisms, exclusion, and bodily functions [12]. In another study by Deutsch-Link et al. [13], essays written by schizophrenic patients included more external referential language and fewer mentions of the word *I* than control subjects.

LIWC has also been applied to transcripts of interviews with schizophrenic patients. A study by Minor et al. [14] consisted of analyzing structured interviews with schizophrenic patients. Interviews were recorded, manually transcribed, and then processed for lexical analysis by LIWC, where *anger* words significantly predicted greater symptoms. Similarly, Hong et al. [15] extracted lexical features to distinguish between schizophrenia patients and controls from manually transcribed speech of schizophrenia patients and control subjects. In their study, the speech of schizophrenic patients featured less usage of *I* and *adverb*, and more frequently included words from the categories of *friend* and *relative* instead, when compared to control subjects.

In all above-mentioned studies, the texts were either written by patients or manually transcribed from audio recordings. In our study, we explored the feasibility of applying linguistic analysis to automated transcriptions of interviews with patients and control subjects, conducted by psychologists. The audio recordings of 71 participants (47 patients and 24 control subjects) were automatically transcribed through speech recognition software. We then apply LIWC to the automatically transcribed text to explore linguistic differences between schizophrenic patients and controls. This research is in alignment with our previous works to develop automated, objective methods to examine behavioral deficits in schizophrenia, in which we studied non-verbal cues related to speech [16] and movement [17].

Speech recognition technology has greatly improved in recent years thanks to the breakthroughs in the domain of artificial intelligence. Many existing APIs support transcription of microphone streams and audio files directly to text files [18]. Dozens of languages are supported by these platforms, but the performance varies as they employ different language models and machine learning algorithms. Generally, it has been observed that Deep Neural Network (DNN) based tools outperform those based on Gaussian mixture models (GMM) [19].

In our analysis, Google Cloud Speech API was utilized to convert the interview recordings to texts. By means of lexical cues, we were able to classify patients and healthy control subjects at an accuracy of 86% (by leave-one-out cross-validation). We discovered that the speech produced by schizophrenic patients featured fewer *informal* words (e.g., okay, coz, oh) and female patients speech more frequently contained *female family* words (e.g., sister, mother). Similar to the findings in [15] and [20], we also observed that schizophrenia patients were more likely to use *feelings* words (especially feeling related to themselves), and less likely to use adverbs in their speech compared to control subjects.

This paper is organized as follows. In Section 2, we describe the experimental design and demographics of the participants. We then elaborate on the steps of our analysis in Section 3, and present the numerical results for speech recognition and linguistic analysis in Section 4. In Section 5, we investigate the most salient linguistic features, and offer our concluding remarks in Section 6.

2 Experiment Design

This experiment is in collaboration with the Institute of Mental Health Singapore (IMH). 71 individuals participated in this experiment. There are two groups of participants: 47 *Patients* who are diagnosed with schizophrenia, and 24 *Controls*, who do not have any pre-existing disorders. The participants are recruited by IMH based on the recommendation of clinicians, and the participants are matched for age, gender, ethnicity, and education. The participants are all above 19 years old, and although they are not native English speakers, Singapore being a multiracial and multicultural country, all of them can communicate in fluent English. The participants have provided written informed consent and receive monetary compensation for their participation in the study. The study protocol has been approved by the National Healthcare Group's Domain-specific Review Board in Singapore. The demographic information of participants is displayed in Table 1.

In this experiment, each participant underwent an interview conducted by a professional psychometrician from IMH. The interview is a semi-structured one where the participants are asked certain fixed questions, but replies to those questions can lead to optional follow-up questions. These questions follow from the Negative Symptoms Assessment (NSA-16) rating instrument, which is 16-point scale specifically designed to reflect on the emotions and activities in the life of a patient suffering from negative symptoms of schizophrenia. Based on their replies, the psychometrician rates the behavior of the participants on the NSA-16 instrument on a scale of 1 to 6, where a rating of 1 denotes no recognizable symptoms and a rating of 6 denotes severe symptoms. There is no pre-determined time limit for the interview, nor role-playing during the interview. On average, the interviews last for around 25 minutes. We analyzed the entire length of the interview recordings. The total length of audio analyzed is about 34 hours.

		Patients (N = 47)	Healthy Controls (N = 24)
Age	Mean (years)	30.4	29.8
	Range (years)	20-49	19-47
Gender	Male	22	10
	Female	25	14
Ethnicity	Chinese	39	20
	Malay	5	3
	Indian	3	1
Education	University	6	4
	Diploma/JC/ITE	26	14
	High School	15	6

Table 1 Demographics of participants.

3 System Overview

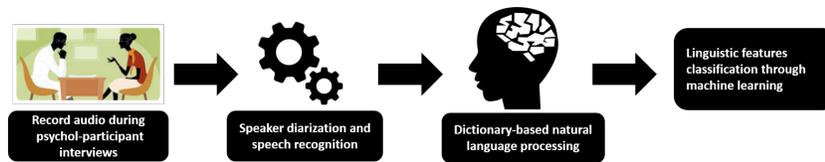Fig. 1 depicts the different steps in our analysis.

Fig. 1 Diagram of the analysis pipeline.

We employed portable equipment to record audio during the interview. Both the psychometrician and patient wore a lapel microphone, and the two audio streams were recorded by an H4n recorder. The two-channel audio recordings were saved in a single .wav file on a laptop. The psychometrician and the participant were seated about 2 meters apart, and this setting minimizes cross-talk from the psychometrician channel onto the participant channel.

3.1 Speaker Diarization and Speech Recognition

The speech of participant and the psychometrician were recorded on separate channels, as mentioned earlier. Nevertheless, there is still some interference from the psychometrician channel onto the participant channel. We apply automated speaker diarization to remove the psychometrician voice from the participant channel. As illustrate in Fig. 2, we extract binary sequences from both speech signals, indicat-

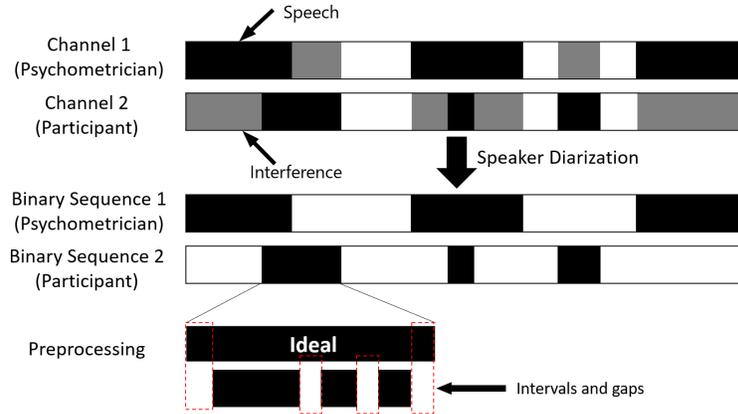ing when the participant and the psychometrician respectively were speaking (0: not speaking; 1: speaking).

Fig. 2 Illustration of speech preprocessing. We first reduce the interference between both audio channels. Channel 1 and 2 are the original signals, from which we derive binary sequences 1 and 2, indicating when the psychometrician and participant respectively are speaking. Next, we apply one-dimensional erosion and dilation to the binary vectors (shown at the bottom of the figure).

To improve the effectiveness of speech recognition, preprocessing is necessary. In order to obtain cohesive speech segments, we apply one-dimensional erosion and dilation to the binary sequence of the participant. Firstly, we dilate the binary sequence 2 by a one-second structuring element, which filled up small gaps (less than 1s) in one speech segment without filling up the adjacent two sentences. Next, we erode and dilate the binary sequence by a two-second structuring element. These steps reduce the noise and incorrect automated transcriptions. At last, we obtain the filtered speech signal, containing mostly speech from the participant, by multiplying the participant audio channel (channel 2) with the binary sequence associated with the participant (sequence 2).

The filtered audio was then subjected to automated speech-to-text API. Currently, many groups and companies provide speech-to-text services, like Google[1], CMU Sphinx[2], and Microsoft[3]. Several speech-to-text APIs were assessed under different audio resources in [21], where Google Cloud Speech API outperformed other speech recognition tools and achieved 9% word error rate. Therefore, we applied Google Cloud Speech API in our analysis.

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[1] https://cloud.google.com/speech/

[2] https://cmusphinx.github.io/

[3] https://azure.microsoft.com/en-us/services/cognitive-services/speech/

3.2 Linguistic Analysis

Following speech-to-text conversion, we applied a dictionary-based method of Natural Language Processing. We counted the different types of words or phrases using Linguistic Inquiry and Word Count 2015 (LIWC). In the classification task, the linguistic extracted from the text were used as attributes in several supervised machine learning algorithms to classify the participants into *Patient* or *Control* groups. We used the Weka tool in JAVA [22] to perform classification with leave-one-out cross-validation. We tested the following classifiers: Support Vector Machine (SVM), Multilayer Perceptron (MLP), Logistic Regression (LR), Multinomial Nave Bayes and 1-Nearest Neighbor (1NN) [23]. Because each feature has specific semantic meaning, and not all features may be relevant to our task, feature selection becomes essential during the classification task. We applied three feature ranking methods: SVM-Recursive Feature Elimination (RFE), Relief Attribute Evaluator (Relief), and chi-Squared Attribute Evaluator [24]. For all combinations of the classifier, ranking method, and the number of top features, we selected the top features of the training data and classified the test data for each fold in cross-validation. We present the classification results for the three ranking methods in Section 4.2. In Section 5, we elaborate on the most salient linguistic features, since they give insight into characteristic behaviors of schizophrenia patients.

4 Results

4.1 Speech Recognition

We measured the performance of Google Cloud Speech API on our dataset. We randomly chose 9 different audio files from our dataset, then extracted the first 5 minutes of each audio to test the accuracy of speech recognition. We determined the number of correct words in every transcription manually. We calculated the accuracies of translation of different APIs by dividing the number of correctly transcribed words by the number of total words (ground truth). The average transcription accuracy and its standard deviation are listed in Table 2, where we transcribed on average 170 words in each file. These results indicate that Google Cloud speech API an average accuracy of about 82% and standard deviation of around 7% (total transcribed words per recording: M = 709).

Speech API	Participant ID									mean	STD
	1	2	3	4	5	6	7	8	9		
Google Cloud	0.87	0.79	0.84	0.84	0.66	0.82	0.78	0.83	0.93	**0.82**	0.07

Table 2 Transcription accuracy of Google Cloud Speech API, tested on 9 random recordings in our dataset.

4.2 Classification

In this paper, we tested several classifiers and feature ranking methods with the normalized LIWC features as attributes and class labels as targets. We present results for the three best-performing classifiers and their ranking method in Table 3. Both SVM and LR yielded the highest accuracy of 86%, which indicated the schizophrenia patients and controls in our dataset can be well separated by lexical features. We discuss the most salient linguistic features in Section 5.

| Classifier | Confusion Matrix | | Precision | Recall | F-score | AUC | Accuracy | Baseline | Ranking method |
	P	C							
SVM	P	45	2	0.85	0.96	0.90	0.81	85.9%	66.2%	Relief
	C	8	16	0.89	0.67	0.76	0.81			
LR	P	41	6	0.91	0.87	0.89	0.87	85.9%	66.2%	SVM-RFE
	C	4	20	0.77	0.83	0.80	0.87			
1NN	P	44	3	0.85	0.94	0.89	0.80	84.5%	66.2%	chi-square
	C	8	16	0.84	0.74	0.74	0.80			

Table 3 Patient (P) vs. controls (C) classification with LIWC features.

5 Discussion

In Fig 3, we show how the classification accuracy varies with the number of linguistic features, for the best classifiers obtained by the three feature selection procedures. The SVM-RFE ranking method yields higher classification accuracy than the chi-square ranking method and leads to the same level of accuracy with fewer features compared to relief ranking method. Therefore, we selected the top 20 features by means of the SVM-RFE. Next, we apply the Kruskal-Wallis Test to these 20 linguistic features, and computed the corresponding p-values. The resulting most salient categories and their p-values are shown in Table 4.

| Words patients used *less* | | | Words patients used *more* | | |
Category	Examples	p-value	Category	Examples	p-value
Informal	netspeak, swear words	0.0029	**Female family**	lady, sister, mom	0.0024
Netspeak	btw, lol, thx	0.0046	**Feel**	feels, touch, anger	0.0602
Assent	agree, ok, yes	0.0056	**Family**	mom, father, wife	0.0935
Adverbs	very, really, quickly	0.0090			

Table 4 Word categories showing with different average counts for patients and healthy controls.

Fig. 3 Classification accuracy of three feature ranking methods as a function of the number of features. The results for the best performing classifiers for each feature selection approach are shown here.

We separated the categories into two classes: the type of words schizophrenic patients used *less* and *more* respectively compared to control subjects. The box plots of the four most salient categories are shown in Fig. 4. We found that patients were less likely to use *adverb* words and *informal* words, which include the *assent* category and *netspeak* category. On the other hand, we found that *female family* words and *feel* words appeared more frequently in the speech produced by schizophrenic patients compared to controls.

We computed the correlation coefficient for *I* and *feeling*, and for *family* and *feeling*; we also conducted the Pearson correlation test. The results of this analysis are summarized in Tabel 5. We can see from this table that schizophrenia patients tend to use both the word I and words related to feelings simultaneously more often compared to control subjects. This effect is also present, yet less pronounced, for the simultaneous usage of family and feeling words. These speech pattern results appear to be in line with the research on social cognitive impairs of schizophrenic patients [27]. Studies have found that due to impairment in social cognition [25, 26], schizophrenic patients tend to focus on themselves, their feelings and thoughts in a conversation, reflecting an inability to perceive, interpret and generate responses to the intentions, dispositions, and behaviors of others [20]. In [15], it was observed that patients were more likely to focus on their own feelings when writing autobiographic narratives as compared to healthy controls.

We also found in our study that the *family* words were more frequently mentioned by schizophrenic patients. It is plausible that for patients, their family mem-
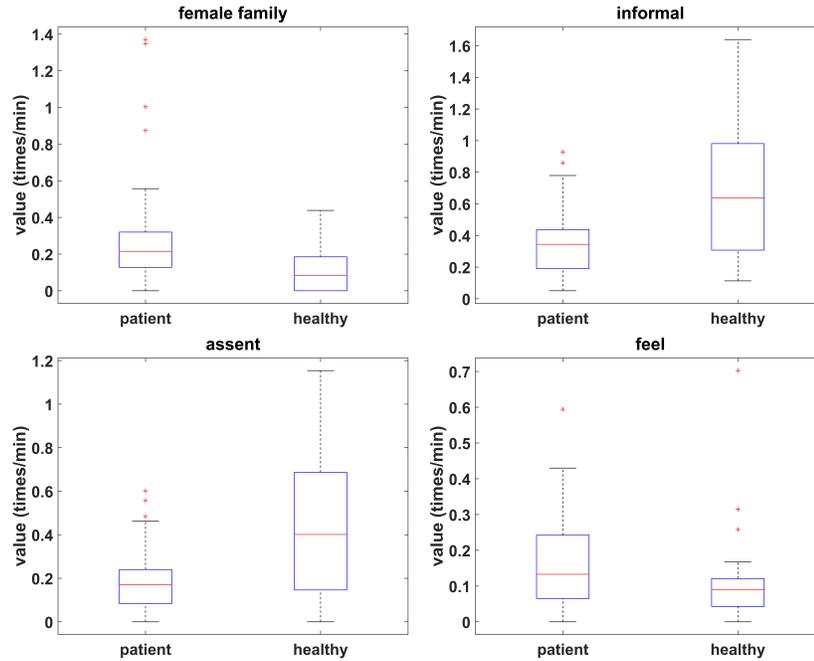
Fig. 4 Box plots of *female family*, *informal*, *assent*, and *feel* categories for patients and healthy controls.

bers are often the ones they interact with the most within their social circles, outside of therapeutic environments. Thus, the frequent mention of *family* is plausible when referencing themselves in the conversation.

	Feeling & I		Feeling & Family	
	Correlation	p-value	Correlation	p-value
Patients	0.648	8.66E-07	0.287	0.05
Healthy	0.5	0.0129	0.026	0.905

Table 5 Correlation coefficients and p-values of the Pearson correlation test for *feeling* vs. *I* and *feeling* vs. *family*.

Studies that investigate differences in LIWC categories in schizophrenic patients and healthy controls often make use of the LIWC 2007 version. *Female* and *informal* are a new category in the 2015 version that we applied here. Therefore, it would be hard to make direct comparisons of the results of this study with earlier studies. In our study, we observed that female patients used far more *female family* vocabulary (mean=0.39 per minute) than healthy female controls (mean=0.1 per minute) as shown in Table 6. This trend did not show up between male patients and healthy

male controls. In Table 7, we further confirm that only female patients used more *female family* words (p=0.00055).

The existing literature suggests that female schizophrenic patients often report higher levels of social support, social functioning, and social withdrawal than male patients [28, 29]. Traditionally, caretaking roles often fall to female members of the family [30], and female caretakers of patients perceive caretaking of their schizophrenic family members more rewarding as well [31]. Consequently, female patients may have greater access and higher proximity to a social support network of female caretakers (aunt, mother, sister), which could account for the higher occurrence of *female family* words in their speech.

	Female family words (per min)				*Male family* words (per min)		
		Mean	**STD**			**Mean**	**STD**
Patient	**Female**	**0.39**	0.37	**Patient**	**Female**	0.22	0.14
	Male	0.17	0.11		**Male**	0.15	0.08
		Mean	**STD**			**Mean**	**STD**
Healthy	**Female**	**0.10**	0.13	**Healthy**	**Female**	0.22	0.32
	Male	0.16	0.16		**Male**	0.21	0.10

Table 6 Word frequency of *female family* and *male family* category on patient and healthy people.

	Female family words	*Male family* words
Female patients	**0.00055**	0.250
Male patients	0.515	0.046

Table 7 Patients v/s Controls p-values of *female family* words and *male family* words.

6 Conclusion

In this paper, we analyzed linguistic features extracted from interviews of schizophrenic patients and healthy control subjects. More precisely, we applied LIWC2015 to provide a dictionary-based words counting method for extracting linguistic features from the audio recordings. We applied several classification and feature ranking methods to distinguish patient and healthy subjects. We obtained an accuracy of 86% for distinguishing schizophrenia patients from healthy control subjects on our dataset of 71 participants. We observed that patients used *informal* and *adverb* words less frequently, but instead used more words correlated to *female family* and *feel*. However, the results are limited by the accuracy of speech recognition, since

the accuracy of converting Singapore English to text is significantly lower than for native English (US and UK). Moreover, the sample size (47 patients and 24 control subjects) is relatively small. More research is warranted to further explore and demonstrate the results of this study. In future work, we will also explore how combining non-verbal and verbal features may provide a more comprehensive characterization of schizophrenia patients.

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