Semantic Coherence in Schizophrenia in Russian Written Texts

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***Abstract*—Schizophrenia is widely known to manifest in language disturbance. Namely, speech incoherence, tangentiality, derailment are indicative of thought disorder characteristic of schizophrenia. Recent advances in distributional semantics have made it possible to measure coherence in text in a unified and objective manner. It has been shown that semantic coherence measures based on distributional semantic models in English speech significantly contribute to schizophrenia diagnosis prediction and correlate with thought disorder measures. However, information on other languages and modes is either contradictory or unavailable. The goal of the current paper is to analyze semantic coherence in schizophrenia in Russian written texts. We present a dataset of short texts written by patients diagnosed with schizophrenia and matched healthy control subjects. We have developed a number of semantic coherence measures, both replicating findings in other languages and novel ones. Our results show that in Russian written texts by patients diagnosed with schizophrenia semantic coherence values are contradictory to the findings obtained for spoken English texts. However, semantic coherence in our dataset provides an effective diagnosis predictor. We discuss our results in terms of possible theoretic interpretation and outline further steps to semantic coherence measurement in schizophrenia.**

I. Introduction

Language impairment in schizophrenia has been viewed as the core symptom since the name of the illness was suggested [1]. Disorganized speech has since been studied both as an individual symptom of schizophrenia and as a manifestation of thought disorder [2],[3].

An important feature to study in schizophrenia and psychosis is semantic coherence in speech: first, it reflects a number of core symptoms of schizophrenia [4],[5],[6]; second, it could be linked to the disturbance in a more subtle way: for example, metaphor is found to be deficient in schizophrenia [7], while metaphor is typically characterized by lower semantic coherence [8],[9]. Lower semantic coherence-based values have been shown to be characteristic of schizophrenia in spoken text in English [4],[6],[10]. German language experiments do not fully support these findings: most of the models were not significant in distinguishing between patients and healthy controls [11]. The question of whether semantic coherence indices are effected by schizophrenia in various languages and settings remains open.

We set out to fill this gap by analyzing semantic coherence in samples of Russian-speaking patients. We present a dataset of short written essays by patients diagnosed with schizophrenia and healthy control subjects. We analyze semantic coherence values by applying a Word2vec model of Russian with part-of-speech tags [12],[13]. In our analysis, the rich morphology of Russian is taken into account, which distinguishes our work from related research in other languages. Moreover, this is, to our knowledge, the first attempt to perform schizophrenia diagnosis prediction based on linguistic profiling in Russian, the first one to analyze semantic coherence in schizophrenia in Russian or in written speech, and the second work to date to address semantic coherence in schizophrenia in a language other than English.

It is important to note that the current research field is by no means aimed at replacing a traditional medical diagnosis. Moreover, in our work we rely on a clinical diagnosis made by psychiatrists. The overarching goal of the current work, as well as the cited research, is to enhance the understanding of cognitive and speech disturbances related to symptoms of schizophrenia, and to provide a broad interdisciplinary view of the phenomena present in the disorder, by applying objective state-of-the-art measures in distributional semantics.

The rest of the paper is organized as follows. Section II describes related work on profiling psychological characteristics of text authors, especially in the Russian language, and the background on linguistic features of schizophrenia, with a focus on semantic coherence. Section III is dedicated to our experiment setting, where we propose a new dataset and introduce our semantic coherence features. In Section IV, results of our experiments on significant feature identification and diagnosis classification of schizophrenia are presented. In Section V, we discuss the obtained results in view of similar finding in related work, and provide possible interpretation directions. Section VI contains our conclusions on the performed experiments and outlines directions for future work.

II. Related work

A. *Author profiling*

In recent years, text-based personality prediction has grown to be a very popular field of study. Especially with the advent of social media resources and the volumes of data they contain, it is now possible to identify automatically a wide range of psychological characteristics [14]. Psychological author profiling is currently performed in a variety of languages [15], including Russian [16],[17].

Linguistic profiling of mental health is increasingly important, as successful text-based identification of mental health disturbances would allow for early diagnosing and formulation of intervention strategies based on psychotherapy. Depression, post-traumatic stress disorder (PTSD), affective disorders and their linguistic markers attract considerable research attention [18],[19],[20],[21],[22]. As a result of this trend, yearly workshops on computational linguistics and mental health have taken place in the recent years: "Computational linguistics and clinical psychology" (CLPsych, 2014-2019, [23]), "Early risk prediction on the Internet" (eRisk, 2015-2019, [24]), dedicated to depression, suicide risk, PTSD, anorexia, self-destructive behavior.

Linguistic profiling of mental health in Russian has been presented by a few works dedicated to PTSD, subjective well-being [25], suicide risk and auto-aggression [26],[27].

Although language disturbance is widely accepted to be characteristic of schizophrenia [27],[28],[29], there have been a few studies in Russian only performing manual evaluation of linguistic characteristics in schizophrenia [30],[31].

B. Schizophrenia and language

Schizophrenia is a disorder characterized by delusions, hallucinations, disorganized behavior, diminished emotional expression or avolition, and disorganized speech [2]. There have been a vast number of attempts to identify the core disturbance in schizophrenia: E. Kraepelin identified schizophrenia as *dementia praecox* and stressed a "peculiar destruction of the internal connections of the psychic personality" [32]; E. Bleuler introduced the term *schizophrenia* and particularly stressed the disturbances of association as the basic symptom, resulting in the loss of speech coherence [1].

Disorganized speech refers to repeated lack of coherence or derailment, and can be viewed as a manifestation of Formal Thought Disorder (FTD) [3]. The linguistically manifest symptoms of FTD include the following:

- Incoherent speech: loss of associations between sentences;
- Tangentiality: irrelevant responses to questions;
- Derailment: loss of association between larger speech units;
- Illogical speech;
- Indirect speech [3].

With the rise of linguistic and neurocognitive science, there have been a number of theories giving language the central role in schizophrenia. J. Lacan [33] introduced a theory of psychosis, including schizophrenia and paranoia, where psychosis is characterized primarily by a disturbance of the symbolic relations between the signifiers and the signified. There are a number of implications of the Lacanian theory of psychosis relevant for contemporary research [7]:

- Deficient metaphor comprehension and use (cf. [34]);
- Autonymic speech, or presence of specific words or expressions with a special meaning to the subject, that their discourse tends to revolve around.
- Dominance of the associations at the level of signifier over the level of signified.

From the neurolinguistic perspective, T.J. Crow has argued that schizophrenia is a result of brain changes attributed to language evolution [35]. This view was further developed with the idea that "schizophrenia is a breakdown of how language configures thought in the normal brain" [28], with evidence that a breakdown of language mediation between form and meaning may account for the major positive symptoms of schizophrenia. An important example is that metaphor and metonymy processing has been shown to contribute to the formation of delusions [36].

C. Semantic coherence research

Semantic coherence measurement stems from topic modelling coherence evaluation [37]. The idea behind topic coherence is that given a symmetric similarity measure between words, an overall score of word similarity can be measured in a list of words. Semantic coherence is measured as similarity between words in a context window in a text, whereas similarity is typically based on a distance metric between word meanings in a distributional semantic space.

In recent years semantic coherence has been effectively applied to a range of cognitive and profiling tasks in NLP, including lexical error identification by learners of English [38], metaphor identification [8],[9]. Experimental evidence suggests that metaphor in both English and Russian is characterized by lower values of semantic coherence, as opposed to direct word meaning. Distributional semantic features have demonstrated author-specificity in authorship attribution tasks [39], including semantic coherence features in Russian data [40].

D. Semantic coherence in schizophrenia and psychosis

Semantic coherence measures based on Latent Semantic Analysis (LSA) in English have first been shown to characterize schizophrenia and FTD by B. Elvevåg and colleagues [4]. The authors performed four verbal experiments with a group of patients diagnosed with schizophrenia with FTD ratings assessed and a healthy control group. The sample volumes were 26/11 patients and 25/10 control participants in two different experiment settings, respectively. The authors used a corpus of 69 MB of text to build a LSA model with 300 dimensions, and applied the model to measuring average values of semantic coherence in the experiment speech samples, as well as coherence between answers and questions. Average semantic coherence has proven to correlate significantly with the diagnosis, FTD ratings, and manual ratings of coherence, tangentiality and content of the answers. Specifically, average semantic coherence values were significantly lower for patients than the control group, and lower for more disturbed patients in terms of FTD. Diagnosis classification results with semantic coherence and a number of additional linguistic features with similarity-based algorithm and cross-validation reached 78% accuracy.

The same LSA model was used to apply semantic coherence features to psychosis onset prediction in a group of 34 youths in high risk of psychosis [10]. 5 of these transitioned to psychosis during a 2.5-year follow-up study, and the rest 29 did not. The participants were asked to describe changes they had experienced and their reaction to them. ~1 hour open-ended interview speech was recorded for every participant. The single significant semantic coherence feature identified was the minimum first-order semantic coherence between two consecutive sentences in the interviews. The individuals who transitioned to psychosis later showed lower values of minimum between-sentence coherence, or higher disorder between their sentences. Semantic coherence with two syntactic features resulted in 100% accuracy in a leave-one-subject experiment with a convex hull algorithm.

The evidence was supplemented by larger participant cohorts and different linguistic measures [5], showing that speech of individuals developing psychosis is characterized by decreased semantic coherence between successive sentences and greater variance in that coherence. The text-based classification accuracy between patients in psychosis and healthy individuals reached 72%.

In a recent work D. Iter et al. [6] attempted to replicate the findings of semantic coherence features in schizophrenia in an English-speaking sample of 9 patients and 5 control subjects. The data consisted of spoken interview answers on everyday questions, with a mean 300 words per participant. They applied the same LSA model, as well as Word2vec and Glove word embeddings, and different normalization strategies, to analyze average coherence between sentences and tangentiality of the responses. A few of the settings resulted in significant ($p < 0.05$) difference in coherence and tangentiality, which were lower for the patients than for the control subjects. However, a more informative feature was the number of ambiguous pronouns, and the three combined features resulted in 86-93% classification accuracy (above the random baseline of 64%).

The first experiment to analyze semantic coherence in schizophrenia in a language other than English is applied to German oral speech [11]. 20 patients and 10 control subjects were asked to perform a Narrative of Emotions task, with a mean of 722 spoken words per participant. The methodology closely followed the experiment by D. Iter [6], with both coherence and tangentiality computed based on Word2vec and Glove. However, mean between-sentence coherence was lower for patients than for control subjects, and lower for positive FTD than non FTD. However, tangentiality values did not differ significantly between groups. One of the reasons for modest results could be the morphological richness of German, whereas no morphological preprocessing was applied in [11].

Existing research gives contradictory evidence on whether semantic coherence is regularly related to schizophrenia in speech. Our study on short written texts in Russian is aimed at supplementing the evidence on semantic coherence features in schizophrenia.

III. Semantic coherence and schizophrenia in written texts in Russian

A. Experiment

The goal of the experiment is to analyze semantic coherence features in schizophrenia in Russian. First, we have collected a dataset of short written texts by patients diagnosed with schizophrenia and healthy control subjects. Second, we suggest nine semantic coherence features based on word embeddings of Russian: we reproduce the features analyzed in English and German and provide three additional metrics.

We first analyze the importance of the suggested features in distinguishing healthy subjects from subjects with the schizophrenia diagnosis by using the non-parametric Mann-Whitney U-test [41]. The Mann-Whitney U-test is used because the sample size is small and most of the features fail to pass normality test. Second, we perform binary classification experiments with leave-one-out cross-validation [42]. We apply the Decision Tree algorithm with specific settings: as we aim at evaluating the contribution of specific features on the classification, we restrict the tree depth to the number of features. Thus we obtain a decision tree with every node representing separation by the values by a single feature.

B. Dataset

The dataset was collected as part of the *RusPersonality* corpus [43]. First, we collected texts by patients with diagnosed schizophrenia. Second, we collected control texts by using available *RusIdiolect* resource [44] and gathering additional texts.

RusIdiolect is a corpus developed in Corpus Idiolectology Lab and aimed at representing a variety of Russian language samples in different modes, topics, genres and situations. The corpus is annotated with a range of author characteristics, including age, gender, and a number of psychological variables. As of July 2019, *RusIdiolect* contained texts by 1,500 authors, and it is constantly expanded. The corpus can be accessed online by a database search form [44], allowing to browse specific text and author annotation variables.

Texts by authors with schizophrenia were gathered at the *Voronezh Regional Psychoneurological Hospital*, Voronezh, Russia between September 2015 and January 2016. Patients diagnosed with schizophrenia, according to the International Classification of Diseases-10 [45] were asked to write an account of their previous day. As the texts were originally hand-written, we transformed them into electronic format by typing them preserving original punctuation, orthography, etc. Finally, all the texts were saved as txt files with UTF-8 encoding.

The texts by patients are very short, and two texts shorter than 10 words were removed. Thus texts by 12 patients were gathered (**Patients-1**). All texts are marked with the patients' gender, and 10 texts are marked with the patients' age.

Texts by control authors were gathered between June 2018 and July 2019. The goal was to gather texts accounting for the previous day of the author with the following characteristics:

- The subjects have no history of mental or neurological disturbance;
- The authors are matched with the patients by gender and age, where possible;
- The authors are asked to write an account of their previous day;
- The text length by patients is matched as closely as possible.

Two male authors in the patient group did not indicate their age, so they were matched by gender with authors from the *RusIdiolect* corpus for the **Control-1** dataset. One female patient was matched by gender and age with an author from *RusIdiolect*. Six more patients were matched by gender and age (+-1 year old) with control authors recruited by an announcement in social networks. Three remaining patients were only matched by male gender, whereas the age of the three remaining controlled authors differed significantly (see statistics of the dataset in Table I).

The text length between the Patients-1 and the Control-1 groups differed significantly ($p < 0.01$, Mann-Whitney U-test). In order to eliminate the effect of text length, we also constructed the second pair of samples: **Patient-2** only includes the 9 longest texts by patients (longer than 24 words), and **Control-2** includes the 9 shortest texts by healthy controls (shorter than 84 words, see statistics of the dataset in Table II). As a result, the text length between the Patients-2 and Control-2 groups did not differ significantly.

TABLE I. STATISTICS OF THE AGE- AND GENDER-MATCHED SAMPLES

	Patients-1	**Control-1**
# of authors	12	12
Gender (male, %)	8 (66.7%)	8 (66.7%)
Age	42.8 ± 6.0	37.3 ± 13.3
Text length (words)	42.2 ± 23.1	145.0 ± 116.1

TABLE II. STATISTICS OF THE TEXT LENGTH-MATCHED SAMPLES

	Patients-2	**Control-2**
# of authors	9	9
Gender (male, %)	6 (66.7%)	8 (88.9%)
Age	43.8 ± 6.0	26.3 ± 11.6
Text length (words)	50.0 ± 21.3	59.7 ± 18.8

Thus we obtained a dataset of short written texts describing the author's previous day, containing 12 texts by patients diagnosed with schizophrenia and 16 texts by healthy control subjects. The dataset is divided into two subsets, controlled by age and gender of the authors or by text length.

C. *Semantic coherence features*

We have applied a number of features based on semantic coherence values of the texts. We have used the Word2vec Continuous Skipgram model by A.Kutuzov et al. [46]. The model is trained with the Russian National Corpus and Wikipedia dump as of December 2017, a combined corpus of 600M tokens. The context window is set to +-2, the resulting dimensionality is 300, and the word frequency cutoff is 40. Besides, every word is supplied with its part-of-speech tag, as defined by MyStem [47].

As our datasets consist of very short texts, often containing a few sentences, the between-sentence semantic coherence is inapplicable in our case. We define semantic coherence as the values of pairwise cosine similarity between words in a sliding window, with the sliding window *n* ranging from 3 to 8 words. The semantic coherence in the sliding window is computed as follows (Eq. 1):

$$\mathrm{Coh(Win)} = \mathrm{Mean}\{\cos(w_i, w_j) \mid w_i, w_j \in \mathrm{Win}, i > j\}$$

Every text is characterized by a sequence of semantic coherence values of $length = l + 1 - n$, where l is the text length in words. For each sequence representing a text, the following features are computed:

Min, Max. The minimum and maximum values of semantic coherence.

Mean, Std. The mean and standard deviation of the semantic coherence values in a text.

Perc10, Perc90. The 10- and 90-percentile of the semantic coherence values in a text.

Relmin. The relative position of the semantic coherence minimum in a text, calculated as the position of the minimum semantic coherence value divided by the sequence length.

WeightedMedian. The weighted median of the sequence, or the position of the line dividing the sequence graph in two equal parts, divided by the sequence length.

MinsProp. The number of local minimums in the sequence divided by the sequence length.

IV. RESULTS

A. *Feature significance*

Table III provides the results of statistical significance test for the values described above between Patients-1 and Control-1. The results are presented for window size between 3 and 8. The groups are compared with the non-parametric Mann-Whitney U-test. The features are marked with *'>'* if a randomly selected value of the feature is likely to be higher for the patients than the control group, and *'<'* if the opposite is true. Only the values for features with at least a tendency for significance are shown ($0.05 < p < 0.1$). Statistically significant features are marked with * ($p < 0.05$) and ** ($p < 0.01$).

In the age- and gender-matched dataset, the semantic coherence features **Min**, **Max**, **10-percentile**, **Relmin**, **WeightedMedian** and **MinsProp** are significant in discriminating between patients with schizophrenia and healthy control subjects. The Wilcoxon signed-ranked test mostly replicates the results on the age- and gender-matched dataset, with a few additional significant features identified. However, this relation might stem from different text length between the two samples. Table IV describes the feature significance measure by Mann-Whitney U-test between Patients-2 and Control-2, the samples matched by text length.

TABLE III. RESULTS OF STATISTICAL SIGNIFICANCE TEST (PATIENTS-1 VS. CONTROL-1)

Window	**3**	**4**	**5**	**6**	**7**	**8**
U-test						
Min	> **	> **	> *	>	> *	>
Max	< *	< *	< *	<		<
Mean						>
Std			<			
10-percentile		> *	> *	> *	> **	> **
90-percentile						
RelMin	< *	< *		<	< *	< **
Weighted-Median		<	<	< *	< *	< *
MinsProp			> *			> **
Text length	< **					

TABLE IV. RESULTS OF STATISTICAL SIGNIFICANCE TEST (PATIENTS-2 VS. CONTROL-2)

Window	**3**	**4**	**5**	**6**	**7**	**8**
U-test						
Min	>	> *				
Max		< *				
Mean						
Std						
10-percentile						
90-percentile	<					
RelMin		< *			<	
Weighted-Median						
MinsProp						
Text length						

In samples matched by text length, only three semantic coherence features for window size = 4 stay significant: **Min**, **Max** and **Relmin**. Their sign with regard to the diagnosis/control classification stays the same throughout the experiments with matched age and gender and matched text length. However, it is worth noticing that minimum semantic coherence in our data is higher for the patients than for the healthy subjects, contrary to results in English previously reported by G. Bedi et al. [10]. On the other hand, maximum semantic coherence is significantly lower for the patients than for the healthy subjects. These facts indicate that patients tend to stay away from the extremes in topic shifts in their texts, although the overall semantic coherence variation, represented by **Std**, does not reflect this consideration (cf. [5]). Mean values (**Mean**) of semantic coherence do not differ significantly between the patients and the healthy subjects, which also contradicts with the results reported for English and German spoken samples [6],[11].

B. Classification

Classification results are presented in Tables V-VII. The best results are highlighted in bold, and the second-best results are shown in italic.

We only present the results for the sliding window values, for which statistically significant differences were observed. For the age- and gender-matched dataset, we only present the results for sliding window size 4 and 8, while the rest of the results are similar or lower in performance. We only present the results for combinations of two features (+ text length), since longer feature combinations do not increase classification performance.

TABLE V. CLASSIFICATION RESULTS FOR THE AGE- AND GENDER-MATCHED DATASET (WINDOW SIZE = 4)

Features	**F1**	**Features**	**F1**
Text length	0.74		
Min	*0.79*	*Min + Length*	*0.79*
Max	0.45	Max + Length	0.66
Perc10	0.67	Perc10 + Length	0.66
Relmin	0.61	Relmin + Length	0.54
Min + Max	*0.79*	Min + Max + Length	0.75
Min + Perc10	*0.79*	Min + Perc10+ Length	0.75
Min + Relmin	**0.83**	**Min + Relmin + Length**	**0.83**
Max + Perc10	0.50	Max + Perc10+ Length	0.50
Max + Relmin	0.67	Max + Relmin + Length	0.71
Perc10 + Relmin	0.54	Perc10 + Relmin + Length	0.58

In our dataset matched by age and gender, a natural and strong baseline was provided by text length (F1 = 0.74), as texts by patients were significantly shorter than texts by healthy control subjects. However, the features **Min** and **Relmin** with sliding window size 4, 8 allowed to considerably overcome the baseline and reach a high F1 = 0.87 for **Relmin** with window size 8 combined with text length, and F1 = 0.83, irrespective of the presence of text length feature, for **Min + Relmin** with window size 4. This corresponds to accuracy values of 0.88 and 0.83, with 3 or 4 misclassified samples out of 24, respectively.

TABLE VI. CLASSIFICATION RESULTS FOR THE AGE- AND GENDER-MATCHED DATASET (WINDOW SIZE = 8)

Features	**F1**	**Features**	**F1**
Text length	0.74		
Perc10	0.66	Perc10 + Length	0.75
Relmin	*0.79*	**RelMin + Length**	**0.87**
WeightedMedian	0.74	WeightedMedian + Length	0.58
MinsProp	*0.79*	MinsProp + Length	0.70
Perc10 + Relmin	*0.79*	*Perc10 + Relmin + Length*	*0.79*
Perc10 + WeightedMedian	0.75	Perc10 + WeightedMedian + Length	0.62
Perc10 + MinsProp	0.75	Perc10 + MinsProp + Length	0.67
Relmin + WeightedMedian	0.66	Relmin + WeightedMedian + Length	0.75
Relmin + MinsProp	0.66	Relmin + MinsProp + Length	0.71
WeightedMedian + MinsProp	0.66	WeightedMedian + MinsProp + Length	0.62

For the text-length-matched dataset, we only present classification results for sliding window size 4, which resulted in three significant features.

TABLE VII. CLASSIFICATION RESULTS FOR THE TEXT-LENGTH-MATCHED DATASET (WINDOW SIZE = 4)

Features	**F1**	**Features**	**F1**
Text length	0.32		
Min	0.66	Min + Length	0.50
Max	0.67	Max + Length	0.55
Relmin	*0.71*	*Relmin + Length*	*0.71*
Min + Max	0.53	Min + Max + Length	0.50
Min + Relmin	**0.72**	Min + Relmin + Length	0.66
Max + Relmin	0.55	Max + Relmin + Length	0.55
Min + Max + Relmin	0.61	Min + Max + Relmin + Length	0.56

In the dataset matched by text length, the latter did not increase any of the feature performance in combination. However, a considerable F1 = 0.72 was achieved by **Relmin** and **Min**, and the single **Relmin** performed almost as high (F1 = 0.71). This corresponds to accuracy 0.72 and 5 misclassified samples out of 18.

V. DISCUSSION

Our experiments on a dataset of short written texts in Russian by patients with schizophrenia and healthy control subjects have shown that semantic coherence measured in a sliding window between 4 and 8 words provides significant features discriminating texts by these two groups. This has been shown by statistical measures of feature significance in the whole dataset, as well as leave-one-out classification with a basic decision tree approach. Our classification results for datasets containing 18 and 24 texts range from F1 = 0.72 to 0.87 (accuracy 0.72 to 0.88), respectively. Directly comparable results presented in related work reach 0.72 and 0.78 accuracy [4],[5], however, these included additional linguistic features not related to semantic coherence.

In our study, the only additional feature applied was text length. The best result was obtained by taking into account the fact that texts by patients are very short comparing to respective control texts matched by age and gender, which is consistent with a consideration that speech paucity constitutes a negative symptom of schizophrenia [10]. The most significant semantic coherence features across our datasets and experimental settings are the minimum value of semantic coherence and the relative position of the minimum in a text.

However, with regards to the semantic coherence feature values, our results mostly contradict those obtained for English-speaking samples [4],[6],[10]. Specifically, in our written-text datasets in Russian **patients with schizophrenia consistently demonstrate a higher value of minimum semantic coherence comparing to the healthy control subjects**. As this is both true for age- and gender-matched samples and for text-length-matched samples, the result cannot be solely accounted for by text length. Probably, the contradiction is due to the difference in the mode of the data: minimum semantic coherence is lower in spoken texts samples by patients with schizophrenia in English; however, in Russian written texts patients demonstrate higher minimum, lower maximum and less extreme values of semantic coherence than healthy subjects. A possible explanation is that written mode allows for more control and a greater amount of planning time by the subjects, resulting in smoother topic shift in texts by patients comparing to healthy subjects.

On the other hand, in view of related findings in linguistic research of schizophrenia, the smooth topic shifts (or no shifts at all) could be indicative of autonymic speech revolving around a single topic. At the same time, higher minimum semantic coherence could correspond to less usage of uncommon and metaphoric expressions. Both metaphor deficiency and autonymic speech have been described in previous works on language in schizophrenia [7],[34]. An extreme case of high coherence values in texts by patients is perseveration, a symptom of FTD involving constant repetition of words and expressions, which results in higher coherence values [11] (see also examples below).

The single best semantic coherence feature across our experiment settings is the relative position of the semantic coherence minimum in a text (**Relmin**). Irrespective of text length, the relative minimum position is significantly lower in texts by patients comparing to healthy subjects. This appears to be related to tangentiality, which is measured as the slope of regression line between an interview question and the response of the subject, with patients demonstrating a steeper slope, or lower coherence occurring sooner in their answers [6].

The lower value of the relative position of minimum semantic coherence could be interpreted as fewer or smaller semantic shifts by patients in the second half of their texts: the patients appear to make an initial topic shift close to the beginning of the text, and stick to the chosen topic throughout the rest of the text. Healthy subjects, on the other hand, tend to develop their discourse actively, especially closer to the end of the text.

To illustrate this consideration, we present the texts characterized by the lowest value of the relative coherence minimum position among patients and the highest value thereof among healthy subjects (the original text in Russian is followed by translation into English):

Patients, lowest **Relmin**: *"В прошлые выходные я была с ребенком в лесу, ребенок бегал, играл, потом мы пошли домой, я накормила ребенка, он играл, потом я уложила спать ребенка и сама легла спать."*

"Last weekend I was in the forest with the kid, the kid ran, played, then we went home, I fed the kid, he played, then I put the kid to bed and went to bed myself."

Healthy control subjects, highest **Relmin**: *"Я проснулся часов в 12. Настроение было почему-то плохое. Сходил в душ, затем позавтракал. На улице был дождь, и на улицу совсем не хотелось. Я включил телевизор и начал смотреть кино. После фильма я пошел на кухню и приготовил себе обед. Пообедав, я решил вздремнуть. Проспал несколько часов и пошел в магазин. Придя из магазина я решил сделать ужин. Плотно поужинав, я сел за ноутбук и сделал реферат по архитектуре. На ночь я посмотрел фильм, сходил в душ и лег спать."*

"I woke up at around 12. For some reason, I was in a bad mood. I took a shower, then had breakfast. It was raining, and I didn't feel like going outside at all. I turned the TV on and started watching a movie. After the movie I went to the kitchen and cooked myself dinner. After dinner, I decided to take a nap. I slept for a few hours and went shopping. After coming back from the shop, I decided to cook supper. After having a good supper, I opened my laptop and prepared an essay in architecture. Before going to bed I watched a movie, took a shower, and then went to sleep."

Limitations. Our study has a number of limitations, which are mostly typical of the research field. First of all, the sample sizes in our datasets are very small, ranging from 9 to 12 patients and the same numbers of healthy subjects. Authors of related research report comparable sample sizes ranging from 5 to 29 [4],[6],[10],[11]. Text samples in our study were very short, ranging from 14 to 390 words. Moreover, in our study the experiment settings were somewhat different between subjects: most of the subjects were asked to write a text by their doctor at the hospital or teacher at the university, whereas those recruited by the online announcement could complete the task at home in their spare time.

These limitations call for careful interpretation and cautious generalization of our findings to new data.

VI. Conclusions and Future Work

Although semantic impairment is accountable for some of the most prominent symptoms of schizophrenia, experimental evaluation of semantic coherence in different languages gives contradictory results. We have addressed this question by collecting a dataset of short written texts by patients diagnosed with schizophrenia and healthy control subjects, and developing a number of semantic coherence features, both replicating previous research in English and introducing novel features.

Our experiments have shown that, although some suggested features are closely related to text length, others are significant in the distinction between texts by patients and healthy subjects. Specifically, we have achieved an accuracy of 0.72-0.88 by using semantic coherence features alone and in combination with text length, which is comparable to or higher than similar results reported for English texts.

Our results are contradictory to previous findings on semantic coherence in schizophrenia in spoken English texts. Namely, in Russian written texts by patients the minimum semantic coherence is higher than that in healthy subjects, contrary to related findings in spoken texts in English. However, the most prominent feature of patients speech in the current dataset is the relative position of the semantic coherence minimum in a text.

Due to the contradictory results across languages and sample size limitations, further experiments with larger sample sizes and various settings are needed to generalize our findings to new data.

In the future work, spoken texts in Russian will be added to our analysis. We will also analyze longer text samples by patients with schizophrenia, allowing to apply between-sentence measures of semantic coherence, which will result in a more direct comparison of feature significance between English, German and Russian languages.

Another direction of our future work will be investigating other types of linguistic features which have been shown to be significant in schizophrenia in English [6],[10], namely, morpho-syntactic features, including parts of speech and pronoun types.

Finally, more data will be added on the severity of positive and negative symptoms of schizophrenia, and the correlations of these ratings with semantic coherence will be analyzed, which will provide more fine-grained insight into semantic disturbances related to schizophrenia.

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