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Archival Report

Selective Insensitivity to Global Versus Local Linguistic Context in Speech Produced by Patients With Untreated Psychosis and Positive Thought Disorder

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ABSTRACT

BACKGROUND: Early psychopathologists proposed that certain features of positive thought disorder, the disorganized language output produced by some people with schizophrenia, suggest an insensitivity to global, relative to local, discourse context. This idea has received support from carefully controlled psycholinguistic studies in language comprehension. In language production, researchers have so far remained reliant on subjective qualitative rating scales to assess and understand speech disorganization. However, recent advances in large language models mean that it is possible to quantify sensitivity to global and local context objectively by probing lexical probability (the predictability of a word given its preceding context) during natural language production.

METHODS: For each word in speech produced by 60 patients with first-episode psychosis and 35 healthy, demographically matched control participants, we extracted lexical probabilities from GPT-3 based on contexts that ranged from very local—a single preceding word: P(Wn | Wn-1)—to global—up to 50 preceding words: P(Wn | Wn-50, Wn-49, …, Wn-1).

RESULTS: We show that disorganized speech is characterized by disproportionate insensitivity to global versus local linguistic context. Critically, this global versus local insensitivity selectively predicted clinical ratings of positive thought disorder, above and beyond overall symptom severity. There was no evidence of a relationship with negative thought disorder (impoverishment).

CONCLUSIONS: We provide an automated, interpretable measure that can potentially be used to quantify speech disorganization in schizophrenia. Our findings directly linked the clinical phenomenology of thought disorder to neurocognitive constructs that are grounded in psycholinguistic theory and neurobiology.

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Since the foundational work of Kraepelin and Bleuler (1,2), clinicians have sought to characterize and understand the disorganized, incoherent language output that defines positive thought disorder in schizophrenia. Positive thought disorder affects approximately 50% of individuals with schizophrenia (3) and is associated with impairments in social functioning (4,5) and reduced overall quality of life (3). Given its prevalence and clinical impact, it is critical to develop objective methods for quantifying positive thought disorder and link these characterizations to its neurocognitive underpinnings.

A key insight comes from clinical observations of patients' speech. In healthy adults, the production of coherent language requires continuous integration of broader contextual constraints (e.g., overarching topics) with local dependencies (e.g., semantic and syntactic relationships within sentences) (see the Supplement, section 2.1, for background). However, in phenomena associated with positive thought disorder, such as tangentiality and derailment, patients seem to lose track of global sources of information even though local relationships within short phrases remain intact (1,6–8).

Empirical evidence for relative insensitivity to global sources of information in schizophrenia comes from tightly controlled psycholinguistic studies using both behavioral and neural measures of word-by-word processing. These studies have shown that during language comprehension, people with schizophrenia are less able to use full global contexts (e.g., long sentences or discourse) to facilitate the processing of incoming words (9–13). In contrast, their ability to use local linguistic context (e.g., directly associated word primes or short sentence frames) remains relatively preserved (9,11,13–16).[a]

Despite these insights into language comprehension in schizophrenia, there have been no reliable methods for

[a]Under experimental conditions that encourage strategic or top-down predictive processing, patients' use of local contexts is also impaired [e.g., (17,18)].

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objectively quantifying sensitivity to context in natural speech production. In the 1960s and 1970s, there were some attempts to evaluate patients' use of context in speech production through fill-in-the-blank cloze (17) completions [e.g., (18–20)] (see the Supplement, section 3.2). However, these methods are time intensive and impractical for large-scale studies and ill suited for isolating sensitivity to global (vs. local) context. Consequently, researchers still rely on relatively subjective clinical rating scales to assess speech disorganization (positive thought disorder) in schizophrenia (6,21–26).

Natural language processing (NLP) methods have emerged as powerful tools for quantifying features of atypical speech in schizophrenia. NLP measures can accurately distinguish patients from healthy control participants [e.g., (27–33); see (34) for review] and predict psychosis onset in high-risk populations (31,35,36). Some measures correlate with clinical ratings of speech disorganization (27,37). However, no single measure has comprehensively captured patients' use of local versus global context or been able to specifically predict positive thought disorder, disentangling it from negative thought disorder, overall illness severity, and medication effects.

Large language models (LLMs) offer a promising new approach for addressing this challenge. Unlike earlier NLP models, LLMs are trained on vast amounts of human language data to generate probabilistic predictions of upcoming text tokens based on prior context (see the Supplement, section 3, for a primer). This enables them to capture a wide range of contextual dependencies, including semantic relationships, syntactic structures, discourse-level constraints, and real-world knowledge. As a result, they can generate remarkably coherent language output.

Therefore, LLMs provide an unprecedented tool for quantifying and understanding how impairments in sensitivity to context contribute to disorganized speech in positive thought disorder. By inputting any transcribed speech sample into an LLM, it is possible to output a precise estimate of each word's lexical probability, the probability of the word given the full set of preceding words: P(Word | Prior Context). Lexical probability has long been recognized as a holistic measure of the relationship between a word and its prior context (see the Supplement, section 2), robustly predicting behavioral (38,39) and neural (40–42) processing in healthy adults [see (43) for a review]. Importantly, LLM-derived estimates of lexical probability correlate strongly with cloze estimates (44–46), as well as with behavioral response times (47,48) and neural activity (45,49) during word-by-word language processing.

Not only can LLMs be used to estimate the lexical probability of each word based on its full preceding context, but they can also estimate probabilities using contexts of varying lengths, from extremely local (e.g., a single preceding word, P(Wn | Wn-1)) to broader global (e.g., 50 preceding words, P(Wn | Wn-50, Wn-49, …, Wn-1)) contexts. In this way, researchers can objectively quantify the relative sensitivity of each word's probability to local versus global context during speech production.

In the current study, we used the LLM GPT-3 to extract lexical probabilities for each word in speech samples from untreated patients with first-episode psychosis (FEPs) and demographically matched healthy control participants (HCs). By focusing on FEPs, we avoided confounds related to varying doses or types of antipsychotic medication. To anticipate our findings, we showed that reduced sensitivity to global (vs. local) context specifically predicted clinical ratings of positive thought disorder. Thus, we introduce an automated, theoretically grounded measure that bridges clinical characterizations of positive thought disorder with a mechanistic understanding of language processing.

METHODS AND MATERIALS

Participants

One hundred six English-speaking participants (36 HCs, 70 FEPs) were included from an ongoing study (ClinicalTrials.gov Identifier: NCT02882204). All participants were between 16 and 45 years old. Exclusion criteria were a history of drug or alcohol dependence over the past year, a history of major head injury (with unconsciousness or seizures), intellectual disability, or uncontrolled medical conditions.

FEPs were recruited from April 2017 to September 2019 by screening all consecutive referrals to the Prevention and Early Intervention for Psychosis Program at the London Health Sciences Centre, Ontario, Canada. Patients were approached within 2 weeks of referral, ensuring that they were in the acute, untreated phase of psychosis, with a mean <0.5 defined daily dose equivalent of antipsychotics at the time of speech assessment [see (50) for full sample details]. A later 6-month consensus diagnosis from 2 research psychiatrists and the primary treatment provider (51,52) indicated that 65 of these participants met criteria for a schizophrenia spectrum disorder, and 5 met criteria for affective psychosis[b]. The Research Ethics Board at Western University approved all study procedures. All participants provided informed consent.

Ten patients and 1 HC were subsequently excluded from analysis because of uncertain parental socioeconomic status (parental SES) (53), which served as an important control variable. Summary data for participants included in the reported analyses are shown in Table 1.

Clinical and Neuropsychological Assessment

Patients' symptoms were assessed using the 8-Item Positive and Negative Syndrome Scale (PANSS-8) (54), condensed from the PANSS (55), by one of two research psychiatrists during the same week when speech data were acquired (intraclass correlation for total scores between two raters, based on 10 participants = 0.91).

In all participants, general cognitive function was assessed using 3 tasks: 1) the Digit-Symbol Substitution Test (working memory and processing speed) (56), 2) the Category Fluency Task (semantic memory and executive function) (57), and 3) part B of the Trail Making Test (nonverbal executive function) (58) (see the Supplement, section 1.1, for details).

Speech Data: Clinical Ratings and Extraction of Lexical Probabilities Using GPT-3

Participants described 3 pictures from the Thematic Apperception Test (59), for 1 minute each. Their speech was recorded and transcribed manually by trained research assistants (see the Supplement, Section 1.2, for details).

[b]Analyses excluding these 5 patients produced the same pattern of results reported here.

Table 1. Demographic Variables and Clinical Measures

	HCs, n = 35	FEPs, n = 60	Statistics
Age, Years	21.68 (3.22)	22.26 (4.34)	$t_{87.56} = -0.74$; $p = .46$
Parental SES[a]	3.09 (1.36)	3.50 (1.27)	$t_{67.36} = -1.47$; $p = .15$
Sex, Female/Male	12/23	13/47	$\chi^2_1 = 1.22$; $p = .27$
PANSS-8 Total	8.00 (0.00)	25.79 (7.08)	$t_{56} = -18.97$; $p < .05$
PANSS-8 Positive	3.00 (0.00)	12.48 (3.14)	$t_{57} = -22.95$; $p < .05$
PANSS-8 Negative	3.00 (0.00)	7.48 (4.45)	$t_{57} = -7.68$; $p < .05$
TLI Total	0.31 (0.40)	1.6 (1.43)	$t_{74.15} = -6.50$; $p < .05$
TLI Impoverishment	0.14 (0.25)	0.58 (0.72)	$t_{80.62} = -4.20$; $p < .05$
TLI Disorganization	0.17 (0.26)	1.02 (1.26)	$t_{67.97} = -5.07$; $p < .05$
DSST Score[b]	69.20 (11.00)	50.20 (13.30)	$t_{82.04} = 7.49$; $p < .05$
Category Fluency (No. Exemplars)[c]	24.70 (7.01)	18.20 (5.12)	$t_{51.99} = 4.41$; $p < .05$
TMT Part B Score	55.10 (14.90)	96.40 (74.40)	$t_{45.40} = -3.50$; $p < .05$
Segment Length[d]	99.41 (35.23)	67.47 (31.63)	$t_{65.17} = 4.42$; $p < .05$
Native Speaker Status, E/O/U[e]	2/33/0	10/48/2	$\chi^2_1 = 1.657$; $p = .20$

Values are presented as mean (SD).

DSST, Digit-Symbol Substitution Test; FEPs, patients with first-episode psychosis; HCs healthy control participants; PANSS, Positive and Negative Syndrome Scale; TLI, Thought and Language Index; TMT, Trail Making Test; SES, socioeconomic status.

[a]UK National Statistics Socio-Economic Classification.

[b]Mean of written and oral scores.

[c]Category/Semantic Fluency: Number of animal exemplars produced.

[d]Mean length of contiguous speech segment (in number of words).

[e]E indicates that the participant was a native English speaker, O indicates that the participant was not a native speaker of English, and U indicates that data on native language were unavailable.

Thought Disorder Ratings

Thought disorder was assessed based on these initial speech transcriptions using the Thought and Language Index (TLI) (26), which was completed by a single graduate-level research assistant under the supervision of a research psychiatrist, both blinded to patient status. We computed summary measures of positive thought disorder ("disorganization") and negative thought disorder ("impoverishment") from these ratings (see the Supplement, section 1.3).

Lexical Probability Estimates

We estimated lexical probabilities using OpenAI's GPT-3 *davinci_002* (60) (see the Supplement, section 3.4, for justification). Transcriptions were first divided into contiguous speech segments, i.e., utterances uninterrupted by experimenter speech. We then standardized spelling across segments and removed nonessential punctuation (see the Supplement, section 4.1, for details). Each individual speech segment was then fed into the OpenAI API (https://openai.com/product) to obtain several types of probability values[c]: an estimate based on all preceding context within the speech segment (Supplement, section 4.2), a baseline estimate based on unrelated scrambled contexts (Supplement, section 4.3), and estimates based on a range of context windows (from 1 to 50 words) (see Figure 1 and Supplement, section 4.4).

Statistical Analysis

Although we fed full strings of context into GPT-3 to extract lexical probabilities, we excluded probability values for function words [defined by the Natural Language Toolkit's list of "stop-words" (60)] and disfluencies prior to statistical analysis (see the Supplement, section 5.1) as we did not expect these probability values to be strongly influenced by global information in either group. In contrast, the probabilities of content words were influenced by both local and global sources of information (see the Supplement, sections 2.1 and 2.3). Therefore, restricting our analyses to content words allowed us to precisely test the hypothesis that patients' sensitivity to global (vs. local) context would be reduced. After these exclusions, the dataset consisted of 19,421 content words (patients: 11,696 words, 47.55%; HCs: 7725 words, 47.98%).

We then log-transformed these probability values, ensuring the validity of our statistical models (Supplement, section 6.1a) and helping us meet the assumptions of linear regression (Supplement, section 6.2). We excluded log probabilities >3 or <3 SDs from the mean (per context condition), resulting in the additional exclusion of 81.10 (SD = 15.36) data points (i.e., probability values) per condition on average.

These final log-transformed and trimmed probability values served as dependent measures for a series of linear mixed effects regressions (LMERs) designed to test our a priori hypotheses. Analyses were conducted in R (61) using lmerTest, version 3.1-3 (62), and lme4, version 1.1-33 (63). LMERs account for clustering in data by incorporating by-participant and by-item (here, "item" refers to a particular instance of a word in a particular speech segment) random effects. For all analyses, we modeled the maximal random-effects structure justified by the data and our theoretical assumptions (64). In cases of nonconvergence, convergence was achieved by changing the optimization algorithm, setting correlation parameters to zero, or (rarely) removing a random intercept from the model (see Supplement, section 7, for details).

[c]Note that by default, LLMs produce probabilities for tokens rather than words; see the Supplement, section 4.1, for details of how we converted token-level probabilities to lexical probabilities using the rule of joint probabilities.

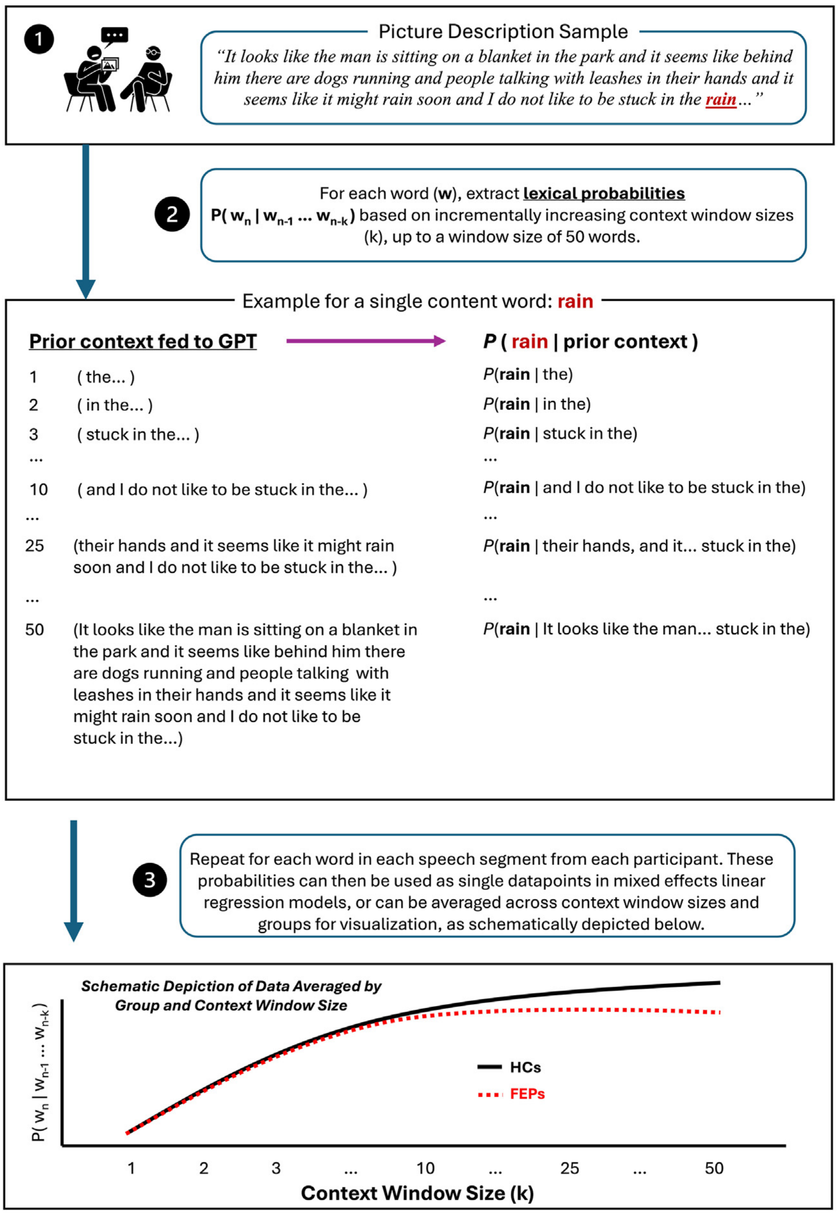

Figure 1. Process for extracting GPT lexical probabilities from participant speech samples given varying amounts of context (1). Speech is transcribed, and spellings and punctuation are standardized (2). For a given word w, we compute its lexical probability given 50 different context lengths, ranging from 1 word P(w_n | w_{n-1}) to 50 words P[(w_n | w_{n-50}) (3). We repeat these computations for each word in each contiguous speech segment for each participant.

In addition to the predictors of interest, all models included two "nuisance" predictors: segment length (number of words in the speech segment), based on the possibility that participants distribute information differently across utterances of different lengths (65–67), and parental SES, which is associated with various aspects of language use [see (68) for a review].

All continuous predictors were z-scored. Thus, fixed-effect coefficients from each LMER correspond to the change in the response variable (log probability) per standard deviation increase in the predictor. See the Supplement, section 6.2(a), for additional discussion of interpreting effect sizes. Results for predictors of interest are shown in Tables 2 to 5; see full results tables (i.e., including nuisance predictors) in the Supplement, section 7. For additional analyses demonstrating the robustness of our main findings, see the Supplement, section 8.1.

RESULTS

Patients Are Generally Less Sensitive to Context During Language Production

To determine whether FEPs were generally less sensitive to context than HCs, we extracted the lexical probability of each word in each speech segment based on the full set of words that the participant had produced up until that point: P(Word | AllAvailableContext) (see Supplement, section 4.2). As a baseline, we

Table 2. Effects of Predictors of Interest for Analyses of Group and ContextType

	Estimate	SE	t	p
A: Effects of Group and Context Type (All Available Context vs. Unrelated Scrambled Context) on Lexical Probability *Model Structure: LexicalProbability ∼ 1 + Group*ContextType + PSES*ContextType + SegmentLength*ContextType + (1 + ContextType | Participant) + (0 + ContextType | Word)*				
Group	−0.23	0.08	−2.72	.01**
Context type	4.63	0.04	109.10	.00***
Context type by group	−0.29	0.09	−3.35	.00**
B: Effect of Group on Lexical Probability, Within the Unrelated Scrambled Context Condition *Model Structure: LexicalProbability ∼ 1 + Group + PSES + SegmentLength + (1 | Participant)*				
Group	0.08	0.08	−0.92	.36
C: Effect of Group on Lexical Probability, Within All Available Context Condition *Model Structure: LexicalProbability ∼ 1 + Group + PSES + SegmentLength + (1 | Participant)*				
Group	−0.33	0.09	−3.54	.00***

See Supplement, section 7, for full results including nuisance covariates, and R code. Model structures are provided in italics beneath each subheading.
$^{**}p < .01$, $^{***}p < .001$.
PSES, parental socioeconomic status.

then extracted the lexical probabilities of the same words but replacing the context (the same number of preceding words) with a set of unrelated scrambled words, randomly selected from a simulated description of an unrelated picture: P(Word | UnrelatedScrambledContext) (see Supplement, sections 1.4 and 4.3). This baseline captured each word's probability in the absence of any kind of linguistic dependency, allowing us to exclude the possibility that group differences in lexical probability were due simply to differences in the words patients used.

Log-transformed lexical probabilities served as the outcome variable in an LMER, with group (between-participants; FEPs = 0.5, HCs = −0.5), ContextType (within-items; AllAvailableContext = 0.5, UnrelatedScrambledContext =−0.5), and the group-by-ContextType interaction serving as predictors of interest (see Table 2, A).

As expected, there was a main effect of ContextType; words were overall more predictable in the AllAvailableContext condition than in the UnrelatedScrambledContext condition. Critically, there was also an interaction between ContextType and group such that the effect of ContextType was smaller in FEPs than in HCs (see Figure 2 and Table 2, A), suggesting reduced sensitivity to context in patients' speech. Within the AllAvailableContext condition, FEPs produced words that were significantly less probable than HCs (Table 2, B). However, in the UnrelatedScrambledContext condition, there was no evidence for any effect of group on lexical probability (Table 2, C).

Table 3. Effects of Predictors of Interest for Analyses of Group and ContextWindowSize

	Estimate	SE	t	p
A: Effects of Group and Context Window Size on Lexical Probability *Model Structure: LexicalProbability ∼ 1 + Group*ContextWindowSize + PSES*ContextWindowSize + SegmentLength*ContextWindowSize + (1 + ContextWindowSize | Participant) + (1 + ContextWindowSize | Word)*				
Context window size	0.81	0.01	82.83	.00***
Group	−0.34	0.09	−3.75	.00***
Context window size by group	−0.08	0.02	−4.04	.00***
B: Effect of Group on Global Lexical Probability (averaged over window sizes from 46 to 50 words) *Model Structure: GlobalLexicalProbability ∼ 1 + Group + PSES + SegmentLength + (1 | Participant)*				
Group	−0.25	0.08	−2.70	.01**
C: Effect of Group on Local Lexical Probability (averaged over window sizes from 1 to 5 words) *Model Structure: LocalLexicalProbability ∼ 1 + Group + PSES + SegmentLength + (1 | Participant)*				
Group	−0.12	0.09	−0.21	.83
D: Effects of Overall Cognition, Group, and Context Window Size on Lexical Probability *Model Structure: LexicalProbability ∼ 1 + Group*ContextWindowSize + CognitiveFunction*ContextWindowSize + PSES*ContextWindowSize + SegmentLength*ContextWindowSize + (1 + ContextWindowSize | Participant) + (1 + ContextWindowSize | Word)*				
Cognitive function	0.01	0.06	0.21	.83
Context window size	0.84	0.02	48.11	.00***
Group	−0.31	0.11	−2.78	.01**
Context window size by cognitive function	0.00	0.01	−0.26	.80
Context window size by group	−0.08	0.03	−3.24	.00**

See Supplement, section 7, for full results including nuisance covariates and R code. Model structures are provided in italics beneath each subheading.
$^{**}p < .01$, $^{***}p < .001$.
PSES, parental socioeconomic status.

Table 4. Effects of Predictors of Interest for Analyses of Positive Thought Disorder (Disorganization) and ContextWindowSize

	Estimate	SE	*t*	*p*
A: Effects of Disorganization and Context Window Size on Lexical Probability (Within Patients)				
*Model Structure: LexicalProbability ∼ 1 + Disorganization*ContextWindowSize + CognitiveFunction*ContextWindowSize + PSES*ContextWindowSize + SegmentLength*ContextWindowSize + (1 + ContextWindowSize ∣ Participant) + (1 + ContextWindowSize ∣ Word)*				
Disorganization	−0.08	0.04	−2.00	.05†
Context window size	0.78	0.01	59.00	.00***
Context window size by disorganization	−0.02	0.01	−2.75	.01**
B: Effects of Disorganization on Global Lexical Probability (window sizes from 46 to 50 words)				
Model Structure: GlobalLexicalProbability ∼ 1 + Group + PSES + SegmentLength + (1 ∣ Participant)				
Disorganization	−0.09	0.04	−2.63	.01*
C: Effects of Disorganization on Local Lexical Probability (window sizes from 1 to 5 words)				
Model Structure: LocalLexicalProbability ∼ 1 + Group + PSES + SegmentLength + (1 ∣ Participant)				
Disorganization	−0.02	0.03	−0.67	.51

See Supplement, section 7, for full results including nuisance covariates and R code. Model structures are provided in italics beneath each subheading. PSES, parental socioeconomic status.

†$p < .1$, *$p < .05$, **$p < .01$, ***$p < .001$

PSES, parental socioeconomic status.

Patients Exhibit a Selective Insensitivity to Global Relative to Local Context

Next, we addressed the critical question of whether FEPs are selectively insensitive to global (vs. local) context by extracting the lexical probability of each word in each speech segment based on varying context window sizes (from 1 to 50 preceding words; see Figure 3 and Supplement, section 4.4). Log-transformed probability values served as our outcome variable, allowing us to directly test whether the group difference in lexical probability became disproportionately larger as the context window size increased (see Supplement, section 6.1a for discussion).

Predictors of interest were group (between-participants; FEPs = 0.5 vs. HCs = −0.5), ContextWindowSize (continuous, within-items), and the group-by-ContextWindowSize interaction (Table 3, A; see Supplement sections 2.3 and 2.4 for theoretical justification for treating ContextWindowSize as a continuum). We log-transformed ContextWindowSize to produce a more linear relationship with log lexical probability (see Supplement, section 6.2).

Consistent with the above analysis, there was a main effect of group: lexical probability was greater in HCs than FEPs at the mean ContextWindowSize (∼22.07 words of context). We also found a main effect of ContextWindowSize: Across groups, as ContextWindowSize increased, lexical predictability increased. Of most theoretical interest, we also found a significant interaction between group and ContextWindowSize (Table 3, A). This was driven by a smaller (less positive) effect of ContextWindowSize in FEPs than in HCs. As discussed in the Supplement, section 6.2, this interaction cannot be attributed to nonlinear distortions in the relationship between probability and context window size, a floor effect, or increased stochasticity/variability in the patient group.

To visualize the data, we averaged the raw (non-log-transformed) probability values by context window size and group (Figure 3). In both groups, the effect of ContextWindowSize

Table 5. Effects of Predictors of Interest for Additional Analyses of Thought Disorder and ContextWindowSize

	Estimate	SE	*t*	*p*
A: Effects of Impoverishment and Context Window Size on Lexical Probability (Within Patients)				
*Model Structure: LexicalProbability ∼ 1 + Impoverishment*ContextWindowSize+ CognitiveFunction*ContextWindowSize +PSES*ContextWindowSize + SegmentLength*ContextWindowSize + (1 + ContextWindowSize ∣ Participant) + (1 + ContextWindowSize ∣ Word)*				
Impoverishment	−0.09	0.05	−1.77	.08†
Context window size	0.77	0.01	57.84	.00***
Context window size by Impoverishment	0.00	0.01	−0.35	.73
B: Effects of Disorganization and Context Window Size on Lexical Probability Over and Above the Effects of PANSS-8 Scores (Within Patients)				
*Model Structure: LexicalProbability ∼ 1 + Disorganization*ContextWindowSize + PANSS8*ContextWindowSize + CognitiveFunction*ContextWindowSize + PSES*ContextWindowSize + SegmentLength*ContextWindowSize + (1 + ContextWindowSize ∣ Participant) + (1 + ContextWindowSize ∣ Word)*				
Disorganization	−0.07	0.04	−1.70	.10
Context window size	0.78	0.02	44.42	.00***
PANSS-8	0.07	0.08	0.93	.36
Disorganization by context window size	−0.02	0.01	−2.80	.01**
PANSS-8 by context window size	0.00	0.02	0.15	.88

See the Supplement, section 7, for full results including nuisance covariates and R code). Model structures are provided in italics beneath each subheading.

†$p < .1$, **$p < .01$, ***$p < .001$.

PANSS-8, 8-Item Positive and Negative Syndrome Scale; PSES, parental socioeconomic status.

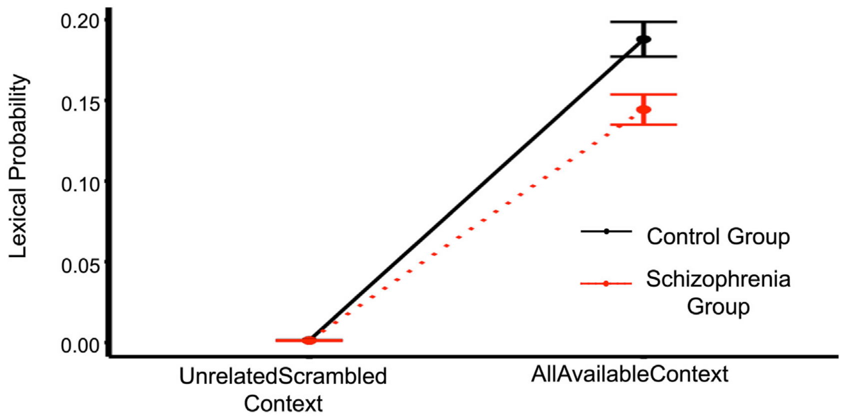

Figure 2. Mean lexical probability by ContextType (AllAvailableContext vs. UnrelatedScrambledContext) in FEPs vs. HCs. Error bars represent one standard error. FEPs, patients with first-episode psychosis; HCs, healthy control participants.

was continuous (i.e., graded), justifying our treatment of the local-global distinction as a continuum. The ContextWindowSize by group interaction effect was also graded: The difference in lexical probability between groups increased gradually as context window size increased.

We also tested for an effect of group at the extremes of ContextWindowSize. For global contexts (averaging across window sizes between 46 to 50 words), we found a significant group difference, as expected (Table 3, B). However, for very local contexts (averaging across window sizes between 1 to 5 words), there was no evidence for a group difference (Table 3, C).

Patients' Relative Insensitivity to Global Context Is Not Driven by Impairments in General Cognitive Function

To determine whether the group-by-ContextWindowSize interaction could be explained by differences in overall cognitive functioning, we averaged the 3 scaled scores from each participant's cognitive assessments. This summary measure (CognitiveFunction) and its interaction with ContextWindowSize were included as additional predictors in the above model (Table 3, D).

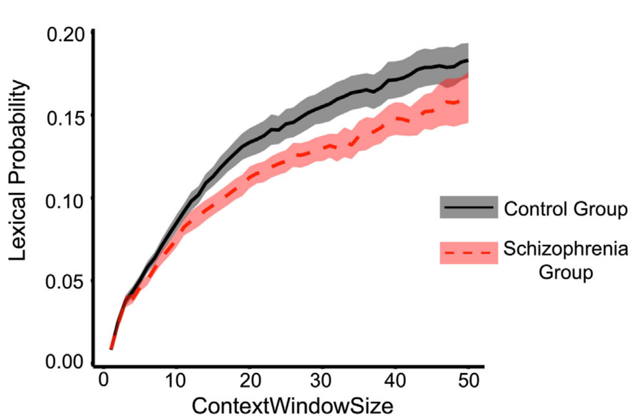

Figure 3. Mean lexical predictability by ContextWindowSize (ranging from 1 to 50 words) for controls vs. patients. Shaded areas represent standard errors. Although both lexical probability and ContextWindowSize were log-transformed in our analyses, we visualize the data here in linear space for interpretability.

As expected, the group-by-ContextWindowSize interaction persisted. In contrast, CognitiveFunction did not predict lexical probability (no main effect of CognitiveFunction), and importantly, it did not modulate the effect of ContextWindowSize (no CognitiveFunction-by-group interaction) (Table 3, D; see Supplement, section 8.3, for exploratory analyses considering individual cognitive scores separately).

Relative Insensitivity to Global Context Is Selectively Associated With Positive Thought Disorder

To understand whether patients' selective insensitivity to global (vs. local) context was linked to clinical ratings of positive thought disorder, we carried out an analysis within FEPs only. Predictors of interest were ContextWindowSize (continuous, within-items), disorganization (TLI summary score; continuous, between-participants), and their interaction (Table 3, A). As expected, the ContextWindowSize-by-disorganization interaction was significant, with greater disorganization predicting a smaller increase in lexical probability as ContextWindowSize increased (Table 4, A and Figure 4; see the Supplement, section 8.2 for exploration of the shape of this effect).

Again, we tested for an effect of disorganization at the extremes of ContextWindowSize. As expected, for global contexts (averaging across window sizes between 46 to 50 words), disorganization significantly predicted lexical probability (Table 4, B). However, for very local contexts (averaging across window sizes between 1 and 5 words), there was no evidence that disorganization was associated with lexical probability (Table 4, C).

To determine whether relative insensitivity to global context was specifically linked to positive (vs. negative) thought disorder, we ran an equivalent analysis but replaced disorganization with the impoverishment summary score (Table 5, A). This revealed only a trending main effect of impoverishment and, crucially, no impoverishment-by-ContextWindowSize interaction.

Finally, to examine the effect of disorganization over and above overall symptom severity, we ran another analysis using the same model as in Table 3, A but also including the PANSS-8

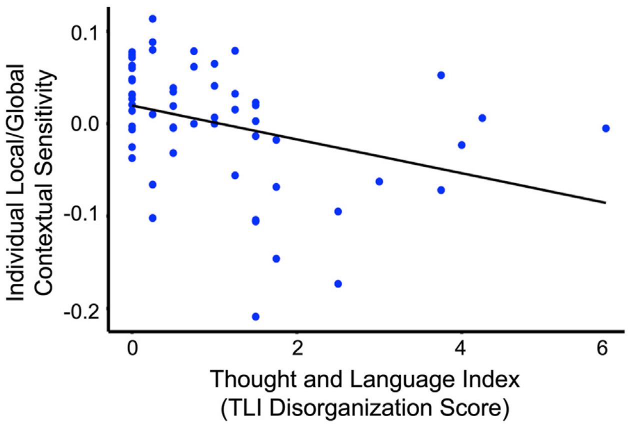

Figure 4. Relationship between speech disorganization, as measured by the Thought and Language Index (TLI) disorganization subscore (a larger score indicates greater speech disorganization) and by-subject local/global bias (i.e., the by-subject slopes for the ContextWindowSize on lexical probability) within patients. The black line represents the regression line of best fit.

total summary score and its interaction with ContextWindowSize (Table 5, B). The disorganization-by-ContextWindowSize interaction persisted. Neither the main effect of the PANSS-8 total score nor the interaction between the PANSS-8 total score and ContextWindowSize was significant.

DISCUSSION

Using the LLM GPT-3, we demonstrated that the speech produced by a large group of FEPs exhibited reduced sensitivity to global (vs. local) context. This reduced sensitivity specifically predicted the severity of disorganized speech in patients. In contrast, we saw no evidence of a relationship with negative thought disorder or overall symptom severity.

Our findings establish a direct link between the clinical phenomenology of positive thought disorder and an interpretable, psycholinguistically informed measure of discourse coherence. During typical language production, sensitivity to the linguistic information encoded in global context is critical for maintaining speech that is coherent to the listener (see the Supplement, section 2.2, for discussion). During language comprehension, lexical probability robustly predicts behavioral (38,39,48) and neural (40–42,45,49) measures of word-by-word processing. By showing that a relative insensitivity to global (vs. local) context selectively predicted clinical ratings of speech disorganization, we provide an objective, automated, theoretically grounded measure that can potentially be used to quantify this key clinical phenomenon.

Of course, it will be important for future work to rigorously test the psychometric properties of this measure, e.g., whether it generalizes across different elicitation conditions (see the Supplement, section 8.3, for preliminary exploration). It will also be critical to understand how other factors (e.g., demographic factors) may or may not be linked to this measure (see Supplement, section 8.1(b), for preliminary exploration). With further validation and development, we suggest that this measure could assist in various clinical applications from diagnosis to symptom monitoring. It may also detect subtle language production atypicalities that are less clinically obvious but nonetheless impact real-world communicative function. Finally, although the current study focused on schizophrenia, the methods that we have used are highly amenable to a transdiagnostic approach, laying the groundwork for examining language atypicalities across diagnostic categories.

Beyond their clinical significance, our findings have implications for neurocognitive theories of positive thought disorder. As discussed in the Supplement, sections 6.2a–d, the observed interaction between context window size and group cannot be trivially attributed to a statistical artifact arising from scaling-related distortions or a floor effect or to a more general impairment in the patient group, such as a more stochastic generative production process. Moreover, although patients performed poorly on the neuropsychological tasks that we administered (Table 1), these general deficits in cognitive function did not explain our findings (Results, section 3). Rather, our results point to a selective impairment in patients' sensitivity to global information, providing a link to a literature on language comprehension, which shows that patients are less able than HCs to use broad schemas and global visual contexts (13) to facilitate word-by-word processing. In contrast, their use of local dependencies (e.g., word-level priming, short clauses or sentences) remains relatively intact (9,11,13–16). Taken together, these findings suggest that the atypicalities observed in language comprehension and production in schizophrenia may stem from shared cognitive and computational principles.

In typical language processing, to explain continuous effects of context, computational theories often invoke a hierarchical structure in which progressively higher layers encode linguistic and nonlinguistic dependencies at increasingly long timescales. At lower levels, lexical items link phonological forms to the meanings of individual words over relatively short timescales; intermediate levels capture syntactic and semantic dependencies that specify "who does what to whom" over medium timescales; and at the highest levels, the overall message connects to broader topic- and schema-relevant knowledge over longer timescales (see Supplement, sections 2.1 and 2.2 for discussion). The central role of lexical probability in language production and comprehension naturally emerges from the incremental use of this hierarchy to optimize lexical processing in a communicative environment: As each word unfolds linearly in real time, its probability is constrained by the contextual dependencies that have already been established at higher levels of the hierarchy.

Context window size therefore serves as a broad proxy for the depth of the representational hierarchy used to modulate lexical probabilities. As the context window expands, lexical probabilities are increasingly likely to be informed by representations encoded over longer timescales. Therefore, our finding that lexical probabilities in patients' speech benefited less from the additional weighting typically conferred by larger context windows is consistent with a selective impairment in maintaining or using higher-level representations.

On the other hand, it is important to recognize that there is no one-to-one mapping between context window size and the representations that inform lexical probability (see the

Supplement, sections 2.3 and 2.4, for discussion). Therefore, our data do not allow us to draw definitive conclusions about the specific types of dependencies that patients can or cannot use during language production. To better understand these representations, we must turn to models that are more transparent than LLMs.

While LLMs have a remarkable ability to output lexical probabilities that closely correlate with human estimates (44–46) and predict behavioral (47,48) and neural (45,49) measures of lexical processing, their "black box" nature limits our understanding of the representations underlying these probabilities (see Supplement, section 3.5). That is, their parameters are not inherently interpretable. Therefore, to comprehensively characterize high-level atypicalities in schizophrenia, it will be essential to develop and use models specifically designed to capture high-level representations (e.g., topics, subtopics, and their boundaries). These models will offer greater transparency for exploring individual differences in patients' sensitivity to various types of global context and linking these differences to distinct subtypes of positive (and negative) thought disorder.

Another key limitation of our LLM-based approach is that it cannot tell us exactly how higher-level representations influence lower-level lexical information during language processing. Most LLM architectures are feedforward in nature, but the human brain is characterized by long-range feedback connections that bridge the highest and lowest levels of the cortical hierarchy and are deeply integrated within the cortical microcircuitry (69). Fully understanding the neural and cognitive dynamics at play in schizophrenia will require the use of a more biologically plausible model.

One promising candidate is hierarchical predictive coding, a type of computational model that 1) commits to a particular arrangement of feedforward and feedback connections prescribing how information flows across the cortical hierarchy and 2) implements a particular type of optimization algorithm that approximates Bayesian inference (70). In the language domain, hierarchical predictive coding has offered key insights into the timing and localization of neural activity across the left-lateralized frontotemporal language hierarchy (71,72).

Conclusions

In a recent work, we developed and implemented a predictive coding model of lexico-semantic processing (73), which explains precisely how local bottom-up and global top-down sources of information interact to dynamically modulate lexical-level activity in healthy individuals. In future work, we plan to use this interpretable, smaller-scale model to understand the precise computational mechanisms underlying patients' reduced sensitivity to global context. This approach will complement the LLM-based methods used in the current study, allow us to directly link these mechanisms to atypical patterns observed across frontotemporal circuits during language processing in schizophrenia (74,75), and situate our understanding of language disorganization within the broader framework of predictive coding research in schizophrenia (76).

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