

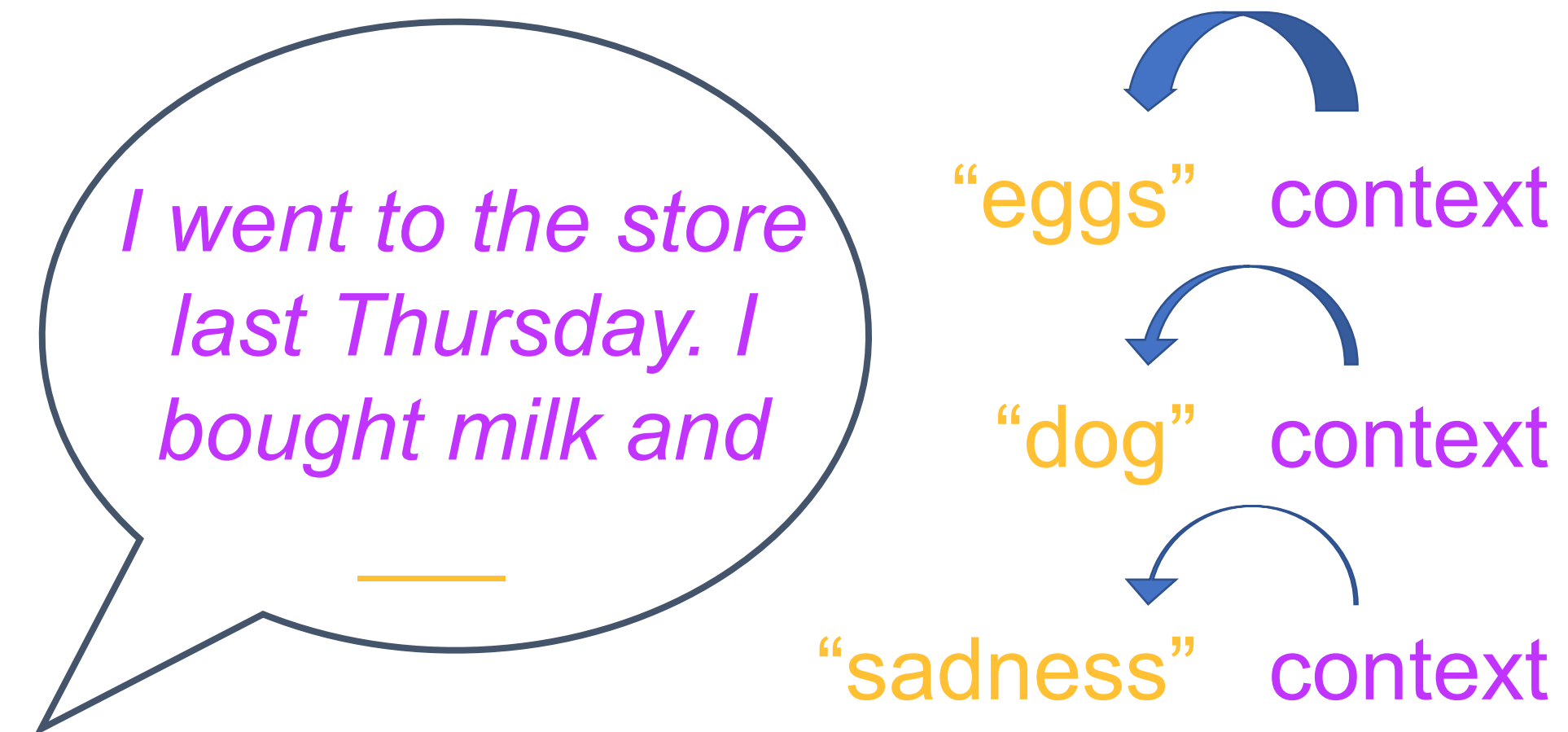
Lexical predictability in schizophrenia: A computational approach to quantifying and understanding thought disorder

INTRODUCTION

Natural speech provides objective, quantifiable data that can potentially serve as a clinical biomarker for schizophrenia & give insight into mechanisms underlying disordered speech

Lexical predictability: probability that a given word will be produced based on its prior context

- In healthy adults, is amongst the best predictors of behavioral processing and neural activity^{a,b,c,d}
- Important role in effective communication^{e,f}



- We used the predictive language model GPT-3^d to quantify word-by-word predictability of natural speech from people with schizophrenia and healthy controls, asking whether:
 - relative to healthy controls, lexical predictability is reduced in the language produced by patients,
 - patients are relatively more impaired in using global versus local context to produce upcoming words, and
 - these abnormalities are linked to clinical ratings of positive thought disorder

METHOD

Data Collection

- 70 patients recruited during their first episode of psychosis^{g,h}
- 36 healthy controls^{g,h}
- 1-minute descriptions of 3 different pictures from the Thematic Apperception Test → 3 unique transcripts per participant
- Participant utterances extracted
 - spellings and punctuation standardized

	Patients	Controls
Age	22.24(SD = 4.37)	21.52(SD = 3.32)
Sex	F: 14; M: 56; NB: 0	F: 12; M: 24; NB: 0
Mean Utterance Length (in words)*	72.80 (SD = 51.74)	94.60 (SD = 56.76)
PANSS Total*	25.48 (SD = 6.86)	8.00 (SD = 0.00)
TLI Total*	1.56 (SD = 1.38)	0.30 (SD = 0.40)
TLI Disorganization*	1.00 (SD = 1.21)	0.16 (SD = 0.26)
TLI Impoverishment*	0.56 (SD = 0.70)	0.14 (SD = 0.25)

* Indicates a significant difference between groups

Data Processing

GPT-3 “davinci-002” predictability was computed for each word of each participant utterance

- First, we gave GPT-3 all available context for each word
- We then manipulated context length within words by giving the model prior contexts ranging from 1 to 50 words in length for each word

Data Analysis

- Excluded disfluencies and function words
- LMERs w/ maximal random effects structures
 - Predictability & Context Length log-transformed
 - Modeled subject-, utterance-, and word-level confounds

“They look like they’re farmers...”
“look like they’re farmers...”
“like they’re farmers...”
“they’re farmers...”

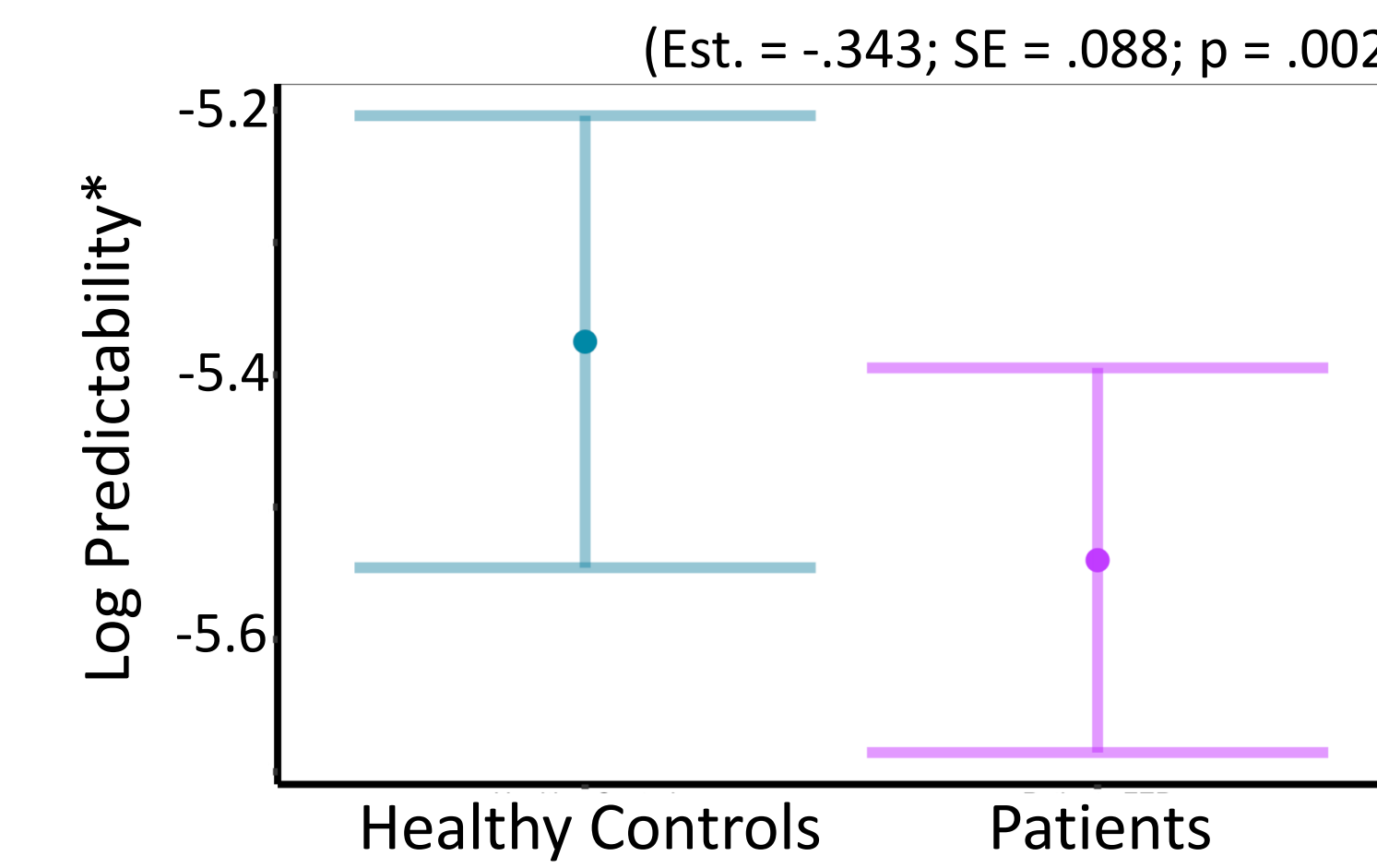


Word	P_1wd	P_2wds	P_3wds	P_4wds	...
They	-	-	-	-	-
look	0.0001	-	-	-	-
like	0.1510	0.1700	-	-	-
they're	0.0002	0.0004	.1812	-	-
farmers	0.0002	0.0003	0.0004	0.0005	-
...

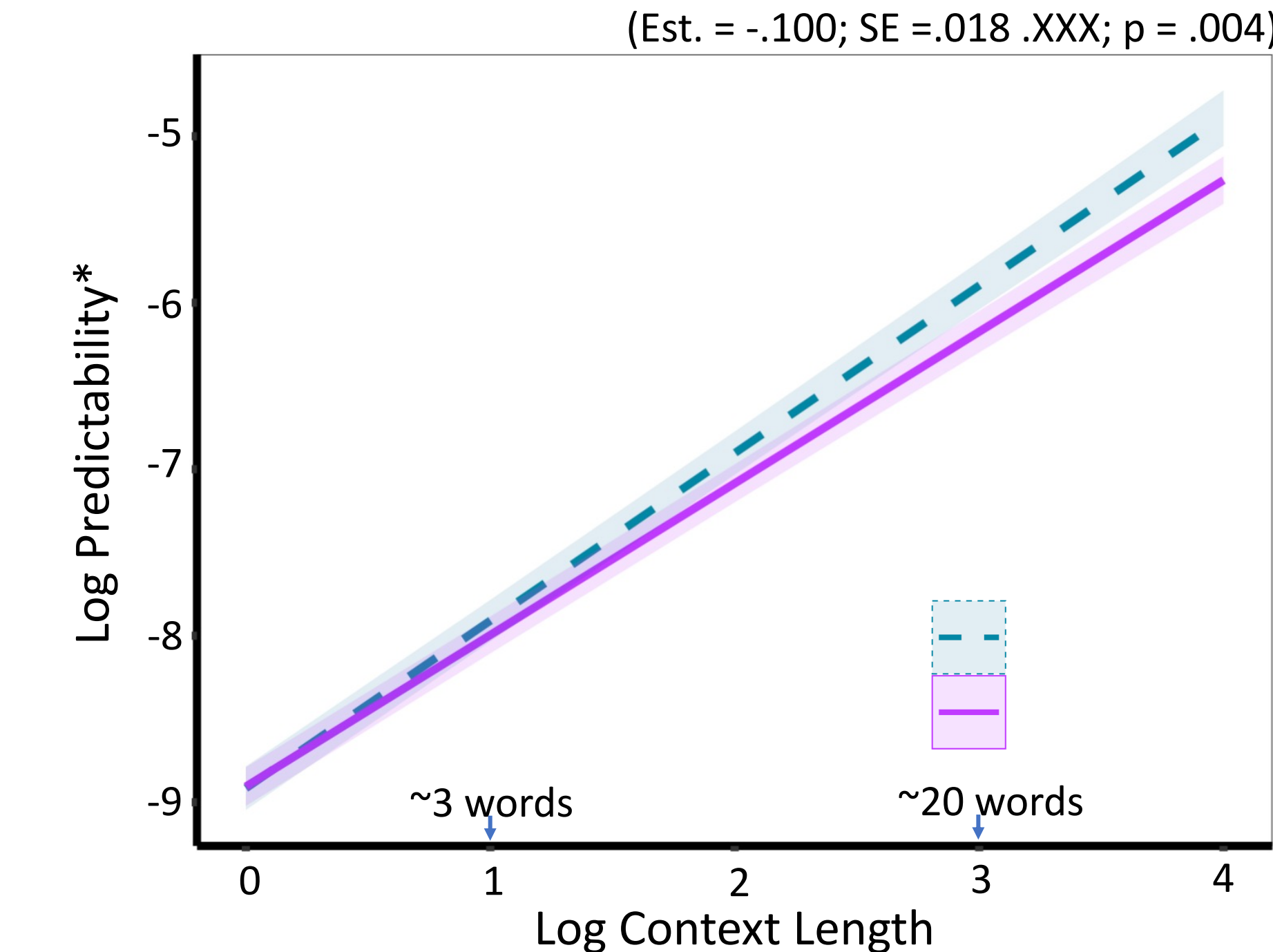
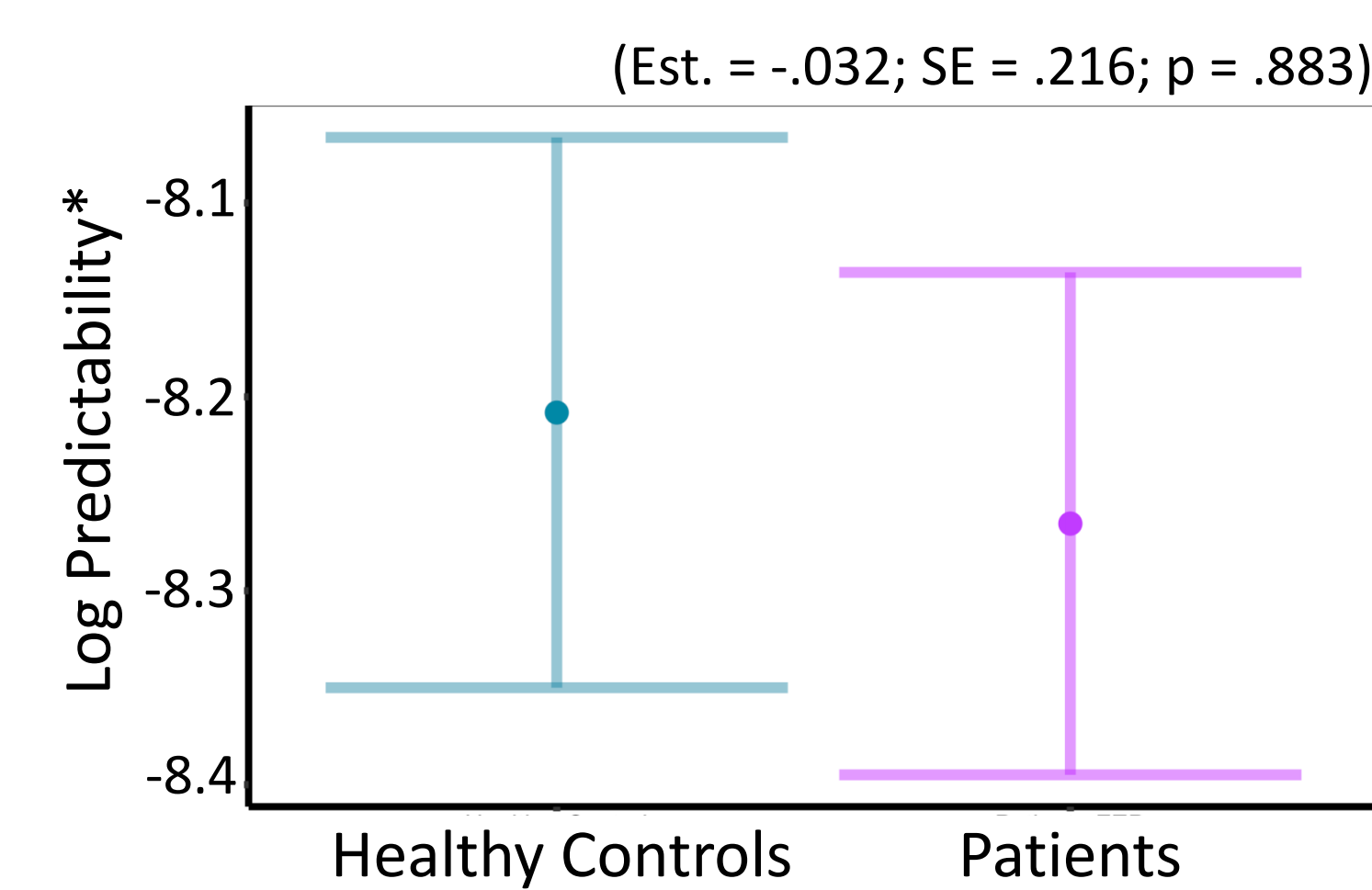
P(“farmers” | “look like they’re”)

RESULTS

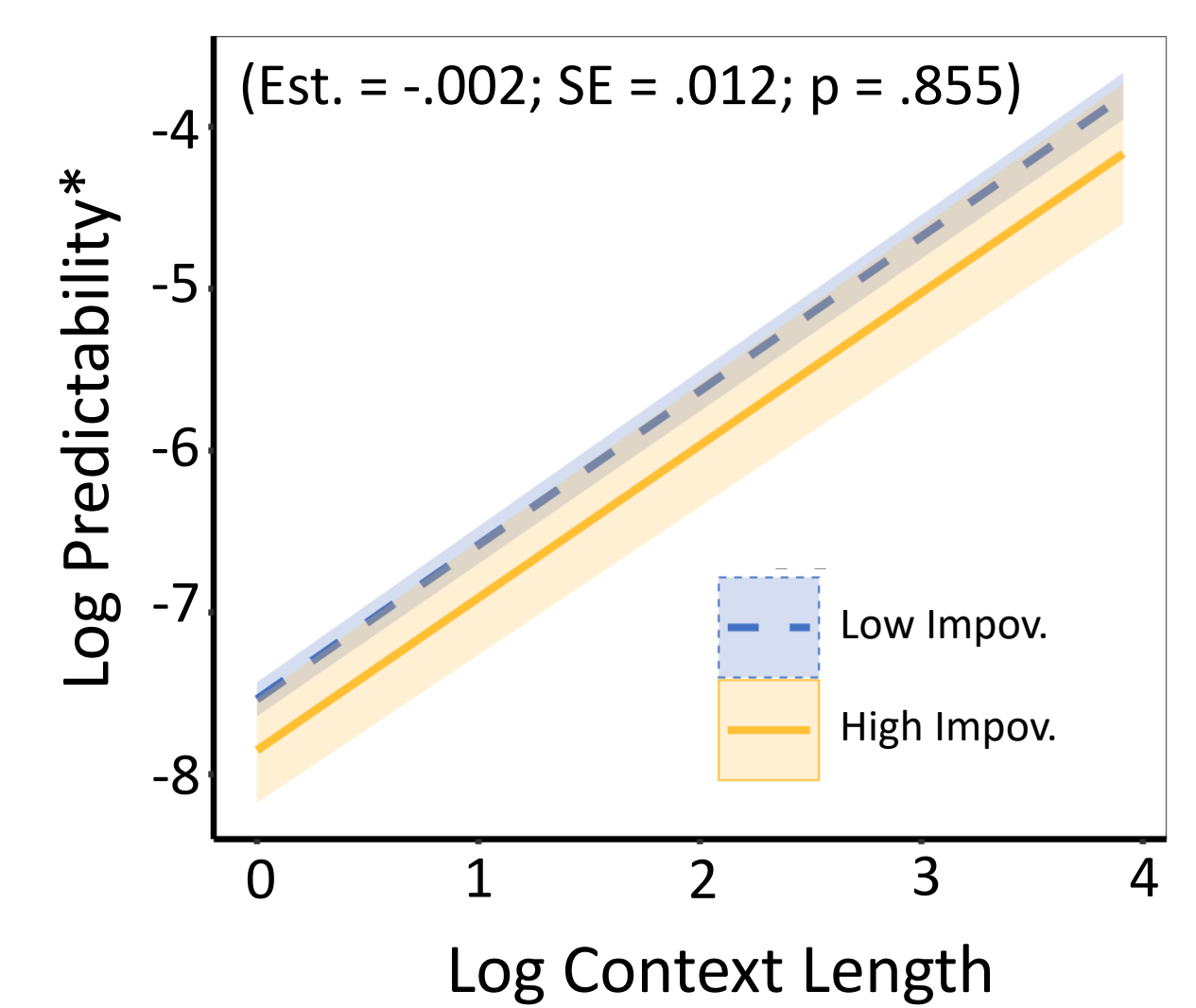
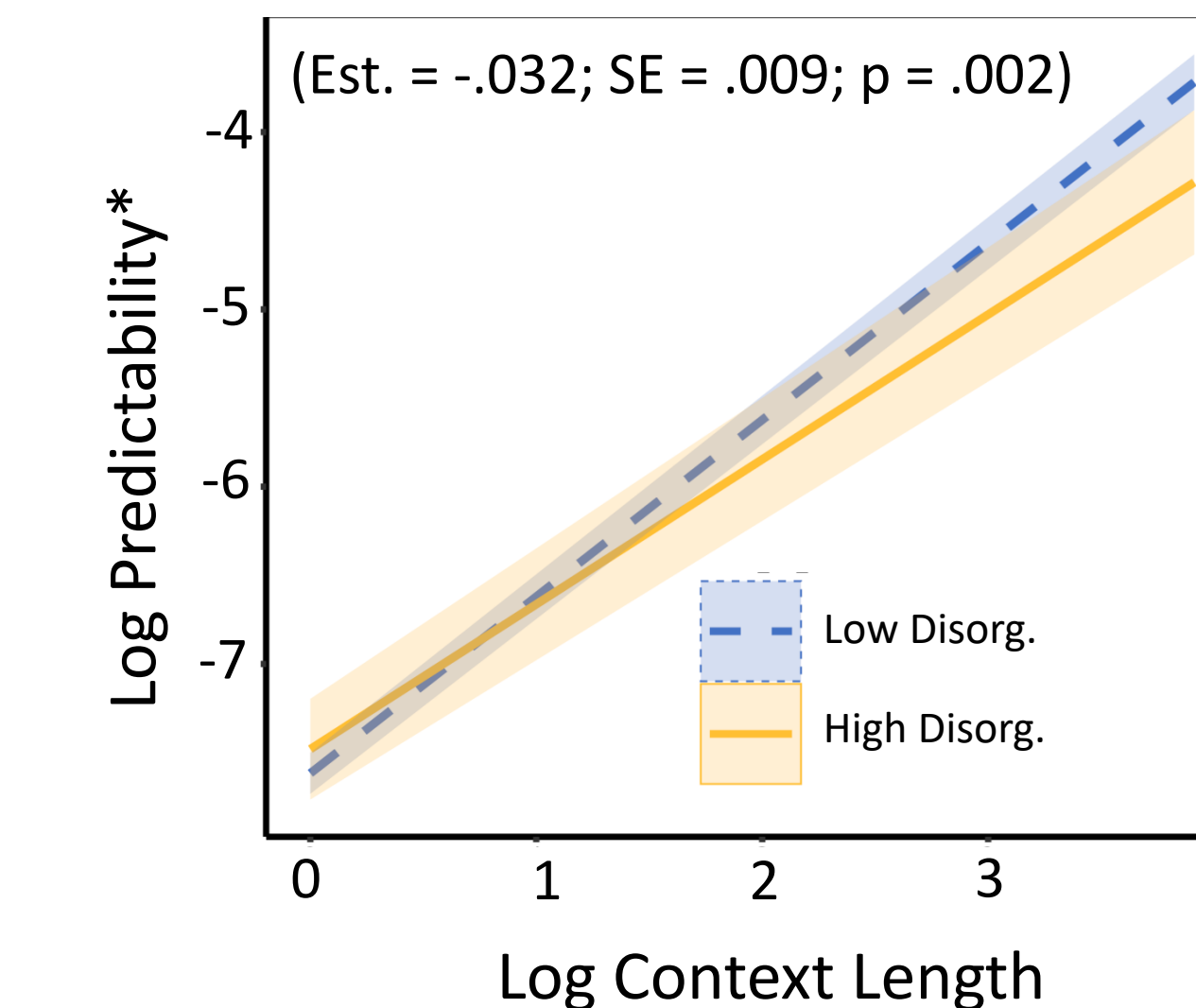
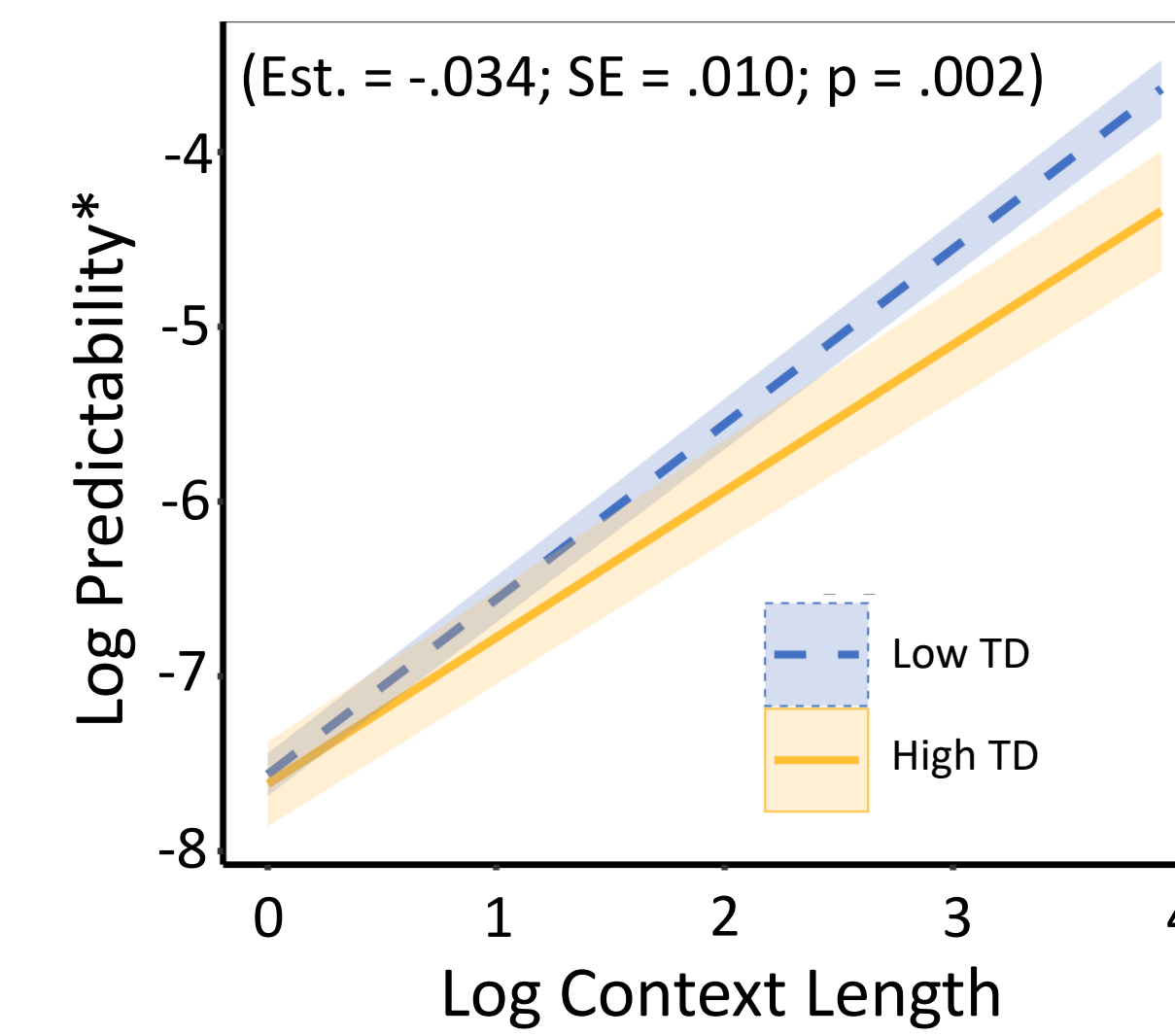
- Overall mean lexical predictability was indeed lower in patients than in controls.



- However, use of very local context appeared to be intact.



- The difference in overall predictability was driven by patients’ failure to increase predictability with additional context to the same degree as in controls (an interaction between Context Length and Group).



- The degree to which use of global context was impaired was linked to overall scores from the Thought and Language Indexⁱ, even after accounting for overall symptom severity
- It was also linked to Disorganization subscores, but not to Impoverishment subscores

* Log Predictability as predicted by the LMER models

CONCLUSIONS

- Our findings suggest that incoherent language output observed in schizophrenia may relate to impaired use of global (vs. local) context to produce upcoming words.
- In line with previous neural evidence showing patients have difficulties using global context to *predict* upcoming words during language comprehension^{j,k}
- Connects to a large body of research documenting abnormalities in predictive processing in schizophrenia across multiple domains^l
- We suggest lexical predictability may provide a useful metric that is easily quantified by computational models, has face validity with thought disorder, and may provide insights into neurocognitive mechanism.

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