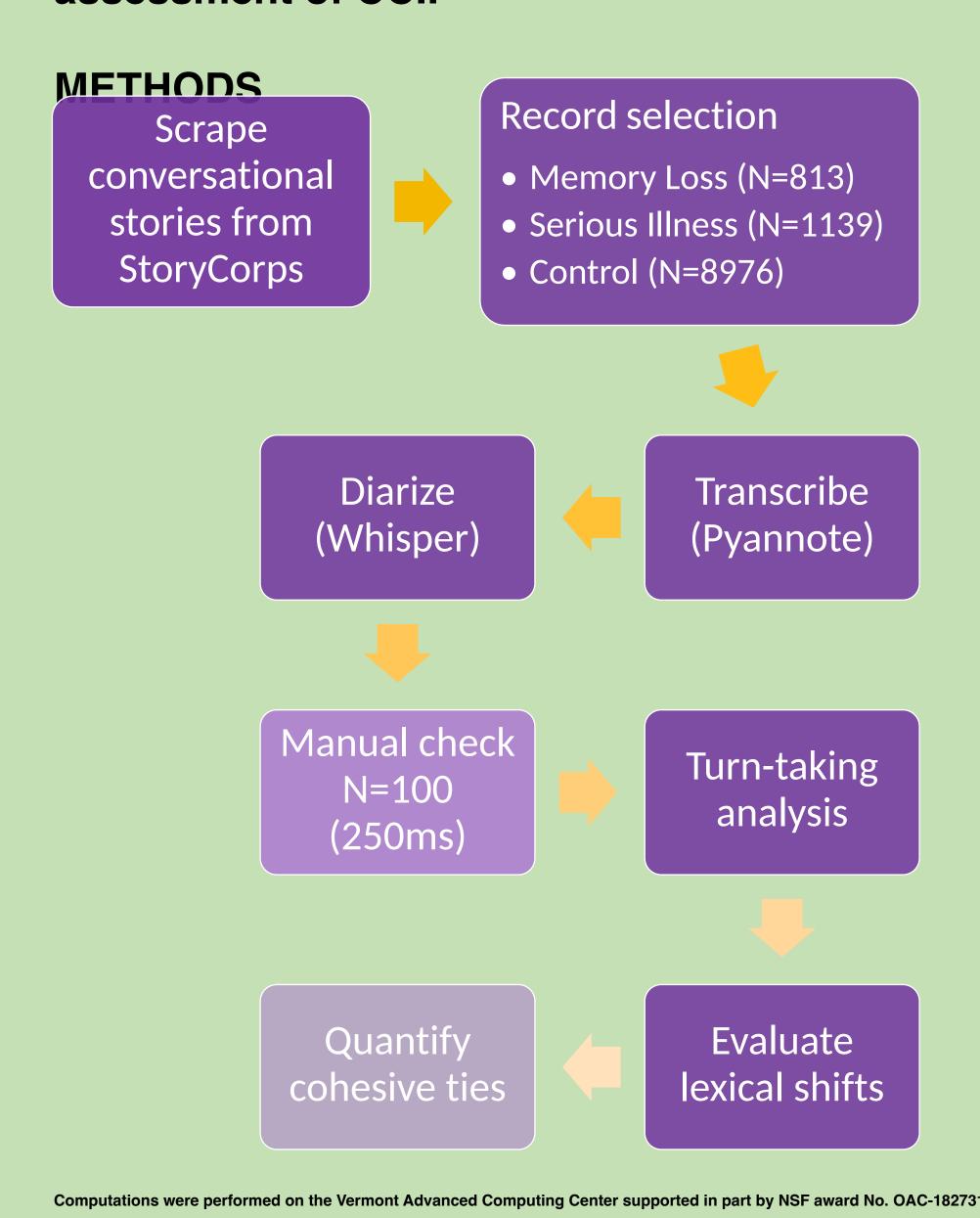
Conversation in the Wild: Automating Analysis for Cognitive-Communication Impairments

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INTRODUCTION

- Brain injury can impact conversational communication. (MacDonald, 2017)
- Assessment and treatment contexts should mirror patient-centered, real-world goals. (Leaman & Archer, 2023)
- Small data sets and behavioral complexity currently limit clinical evaluation strategies. (Sohlberg et al., 2019)

We sought to quantify clinically relevant features of natural conversation that could be normed and automated for diagnostic assessment of CCI.



RESULTS

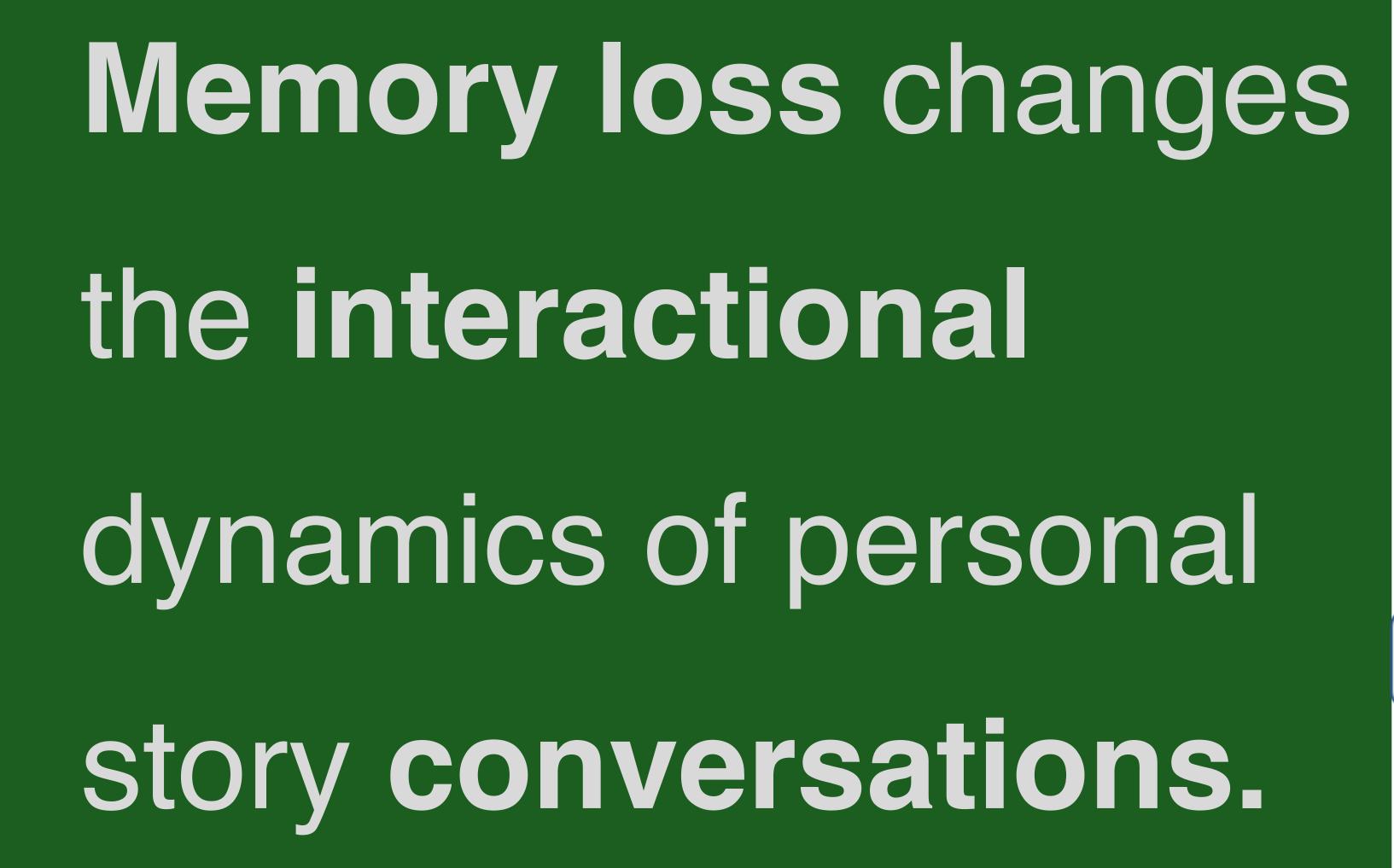
- MemoryLoss turn fq (min) > Control p<0.001
- MemoryLoss turn length < Control p<0.001
 Difference between partners' turn length (sec):
- MemoryLoss Spkr Diff > Control p<0.001
- MemoryLoss Spkr Diff> Legacy p=0.001

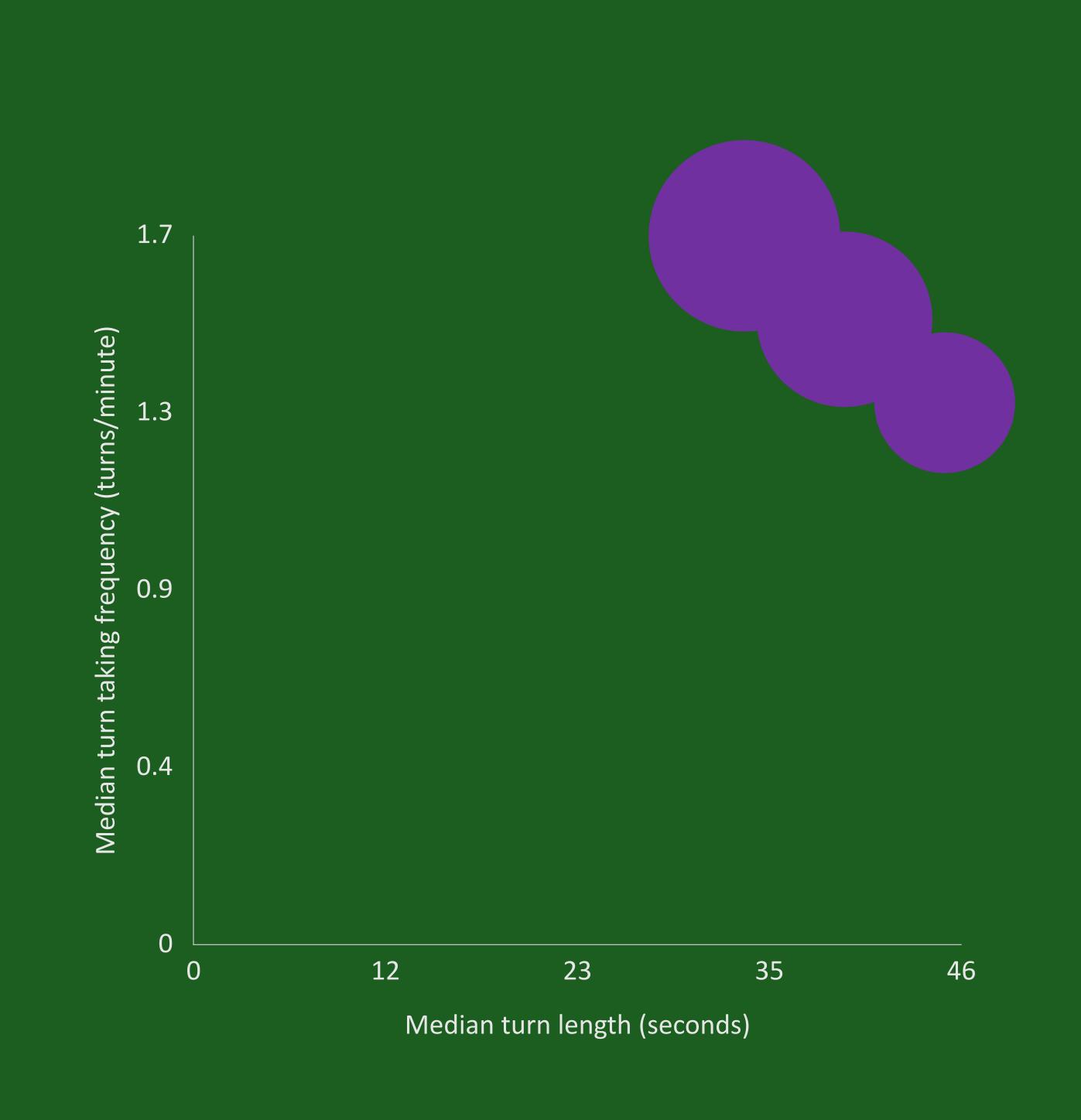
DISCUSSION

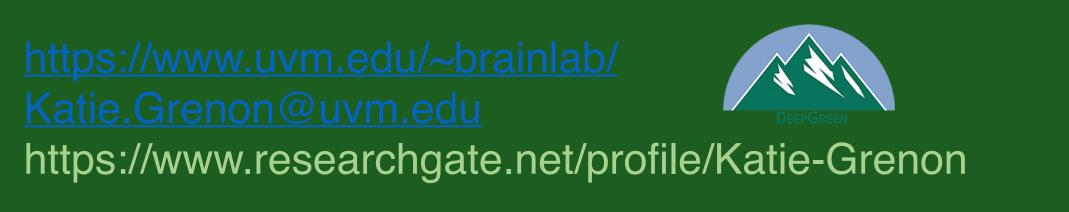
Automated measurement of dyadic communication provides critical insight into the emergent interactional behaviors that characterize natural conversation. These data are not obtainable through traditional monologic assessment.

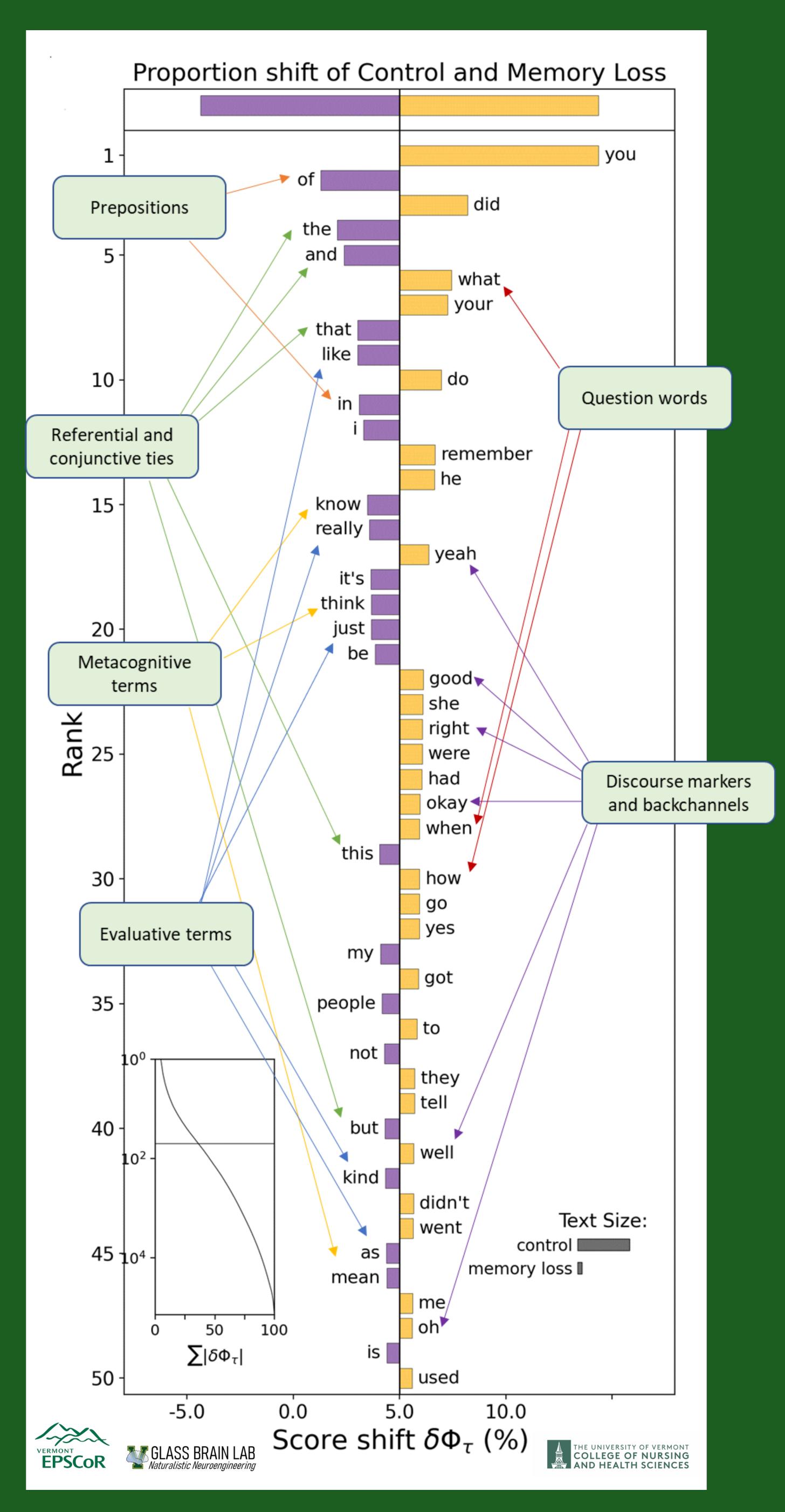
CONCLUSION

We show potential for meaningful naturalistic clinical discourse-norming with **generalizable**









THE WEEDS

Our dataset: >30,000 conversations @ Library of Congress. "To collect, archive, and share the stories of people from all backgrounds because everyone's stories deserve to be heard."

Standard clinical dataset: DementiaBank research corpus including "Cookie Theft" monologs. Largest study thus far included 243 control/309 dementia samples recruited from research studies.

TURN TAKING DYNAMICS

Group	Turn Freq	Turn Length	Length Diff
Memory Loss	1.7	33	50
Serious Illness	1.5	39	42
Control	1.3	45	27
"Turn frog" is the modian # turns/minute "Turn Longth" is the modian longth of			

"Turn freq" is the median # turns/minute. "Turn Length" is the median length of turns, in seconds. "Length diff" is the median difference in average turn length between partners, in seconds.

DATA DRIVEN ANALYSIS

ML conversations are characterized by increased use of partner cues including framing questions and backchannel responses that structure concepts and encourage a speaker to continue. This is also evident in "You" > "I"

ML conversations also show signs of ↓ syntactic and conceptual complexity. In comparison to controls, there are fewer demonstrative and conjunctive ties, fewer prepositions, and less present tense and evaluative language.

IN PROCESS

Word and diarization error rates, Speaker labeling, age & sex matching using propensity scores, validation set analysis.

STRENGTHS AND LIMITATIONS

Secondary analysis limits control over task instructions, recording environment, and demographic info. Automated transcription and diarization affect accuracy.

Promisingly, we obtained significant, meaningful findings even amidst the noise. This suggests that field deployment of an automated assessment could remain feasible and acceptably precise even without ideal implementation.

FUTURE DIRECTIONS

TBI group via metadata Acoustic measures

Dynamic conversational synchrony

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