Profiling temporal patterns of connected speech in post-stroke aphasia using a semi-automated approach

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Connected speech analysis in aphasia

- Critical component of diagnostic assessment[1-3]
  - Functional, ecologically valid, and clinically feasible
  - Increasingly used in research in part thanks to large, publicly available databases of patient recordings, e.g., AphasiaBank
- Captures both **what** is said and **how** it is said
  - What: macrolinguistic, microlinguistic measures[4,5]
  - How: temporal, prosodic measures[6,7]
- **Temporal patterns** in connected speech
  - Timing of speech, as measured by detailed speech/pause measures

1. Fromm et al., *Aphasiology* (2022)
2. Wilson et al., *Brain* (2010)
3. Fromm et al., *Semin Speech Lang* (2020)
4. Andreetta et al., *Neuropsychologia* (2012)
5. Stark et al., *JSLHR* (2023)
6. Haley et al., *JSLHR*, (2021)
7. Cordella et al., *Aphasiology* (2107)

Temporal patterns of connected speech

- Important contributor to overall fluency and communication efficiency
  - Also negatively impacts listener judgments of likeability & competence[1,2]

- Reliance on coarse metrics, but mounting evidence for diagnostic potential of more detailed metrics:
  - Pause types (short, long); pause location[3,4]
  - Subcomponent speech rate measures[5,6]

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1. Harmon et al., *Aphasiology* (2016)
2. Park et al., *Aphasiology* (2011)
3. Angelopoulou et al., *Neuropsychologia* (2018)
4. Mack et al., *Neuropsychologia* (2015)
5. Wilson et al., *Brain* (2010)
6. Cordella et al., *Aphasiology* (2107)

Current study

- Evaluate whether detailed rate/pause metrics can robustly differentiate subgroups of PWA
- Semi-automated approach to extract temporal features
  - Greater promise for clinical feasibility
  - Constrains metrics used for analysis → rate and silent pauses only

Study aims

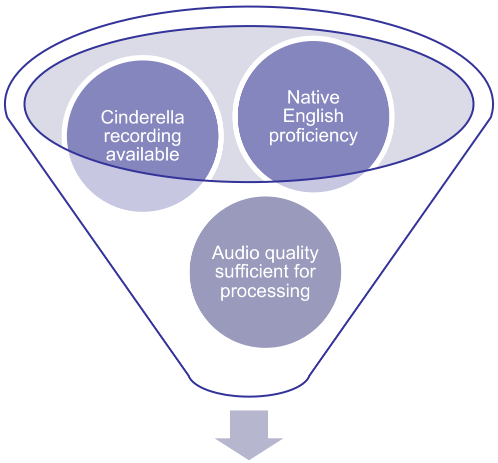
1. Examine groups differences (/correlation) across rate and silent pause measures for PWA belonging to the following categories:
   i. fluent v. non-fluent
   ii. WAB-R aphasia subtypes
   iii. WAB-R Fluency subscores

2. For groups (i)-(ii), characterize and compare cumulative silent pause duration distributions to identify differential patterns

Methods

Participants

AphasiaBank recordings



208 persons with (post-stroke) aphasia (PWA)

3 different fluency grouping schemata

Fluent v. non-fluent (binary clinician gestalt)

WAB-R aphasia subtypes

WAB-R Fluency subscores

Basic Demographics	
mean age (range), yrs	61.8 (25.6 – 90.7)
mean YPO (range), yrs	5.5 (0.08 – 30)
male:female	118:90
mean WAB-R AQ (range)	71.6 (21.4 – 93.4)

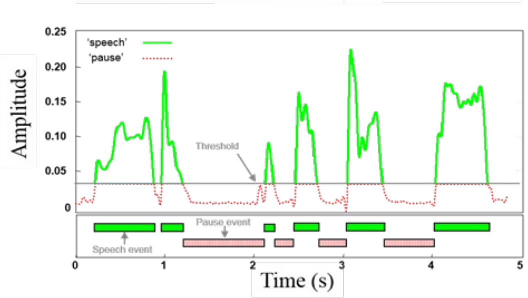
Methods

Audio Processing Pipeline

1 Cinderella audio extracted, cross-talk excised

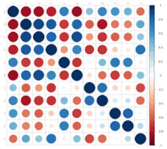
2 Audio noise-reduced (Audacity)

3 Custom MATLAB-based Speech Pause Analysis (SPA) software is used to automatically detect speech vs pause segments (Green et al., 2004)



speech threshold = **25 ms**
pause threshold = **200 ms**

4 14 measures originally extracted following promising results in prior literature → reduced to **10 measures** following correlation-based feature selection (Aim 1)



5 From SPA, (i) extracted durational values (ms) per pause per sample; (iii) log-normalized pause data; (iii) generated cumulative pause distribution densities analysis (Aim 2)

Methods cont'd

Temporal measures

Measure	Derivation/description
total duration	Total length (s) of sample, incl. speech + pause
speech rate*	# words / total duration (words/s)
articulation rate*	# words / speech duration (words/s)
percent pause	(pause duration / total duration)*100
mean pause duration	mean (individual pause event durations, s)
normalized pause count	# pause events / total duration
mean speech duration	mean (individual pause event durations, s)
normalized speech count	# speech events / total duration
coefficient of variation (cv) of pause duration	cv (mean pause duration) ***variability** (↑cv, ↑variability) in pause duration*
coefficient of variation (cv) of speech duration	cv (mean speech duration) ***variability** (↑cv, ↑variability) in speech duration*

*Rate variables calculated w/r/t total word count using CLAN FREQ command on paired CHAT transcripts

Statistical Analyses

Aim 1

Fluent v. non-fluent (binary clinician gestalt) — t-tests, Benjamini-Hochberg (BH) correction for multiple comparison

WAB-R aphasia subtypes — ANOVA, BH correction + post-hoc Tukey

WAB-R Fluency subscores — Kendall rank correlation

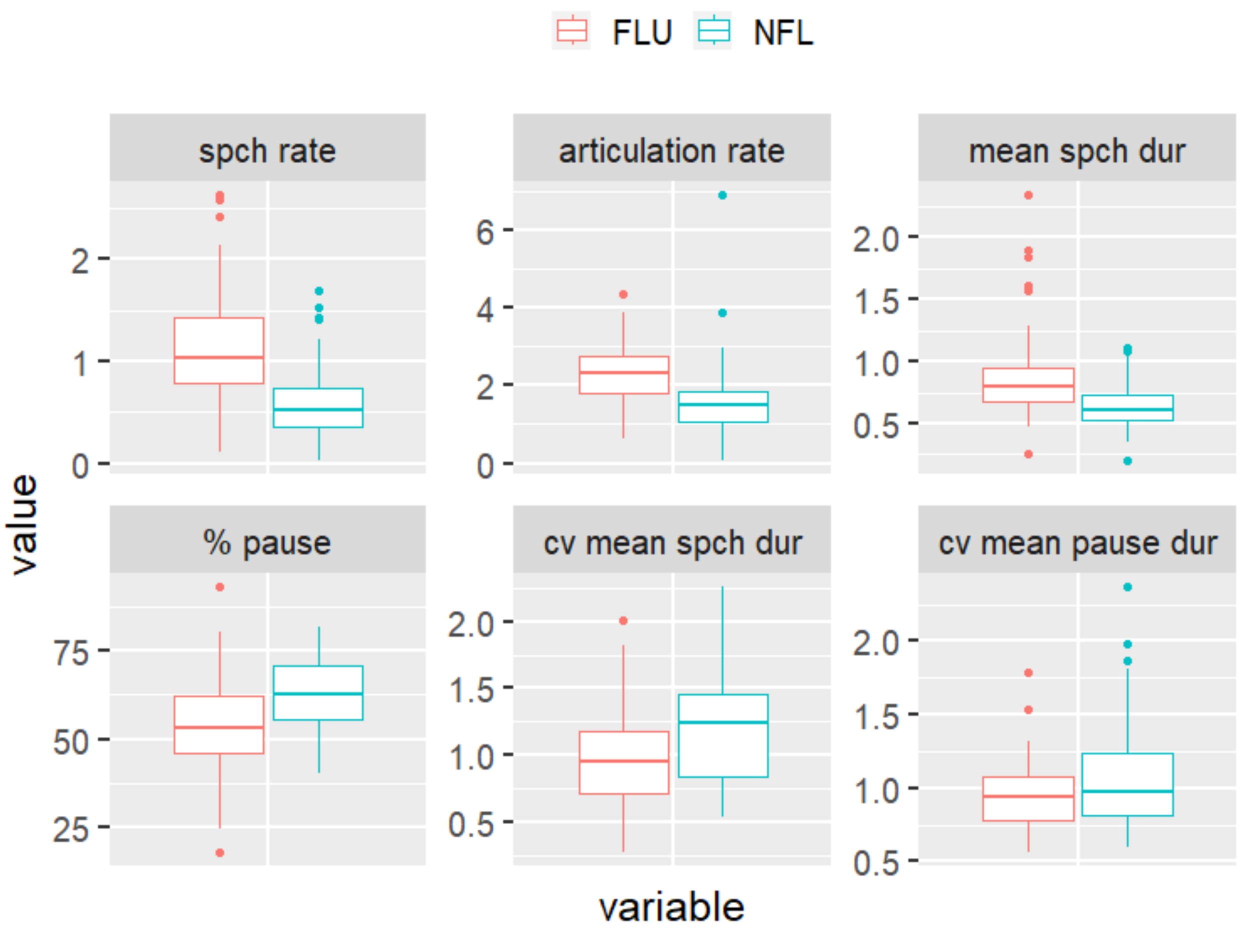
Aim 2

Kolmogorov-Smirnov (KS) tests to evaluate difference in pause distributions, correction for multiple comparison as needed

1010
1010

Fluent v. non-fluent
(binary clinician gestalt)

Results, Aim 1



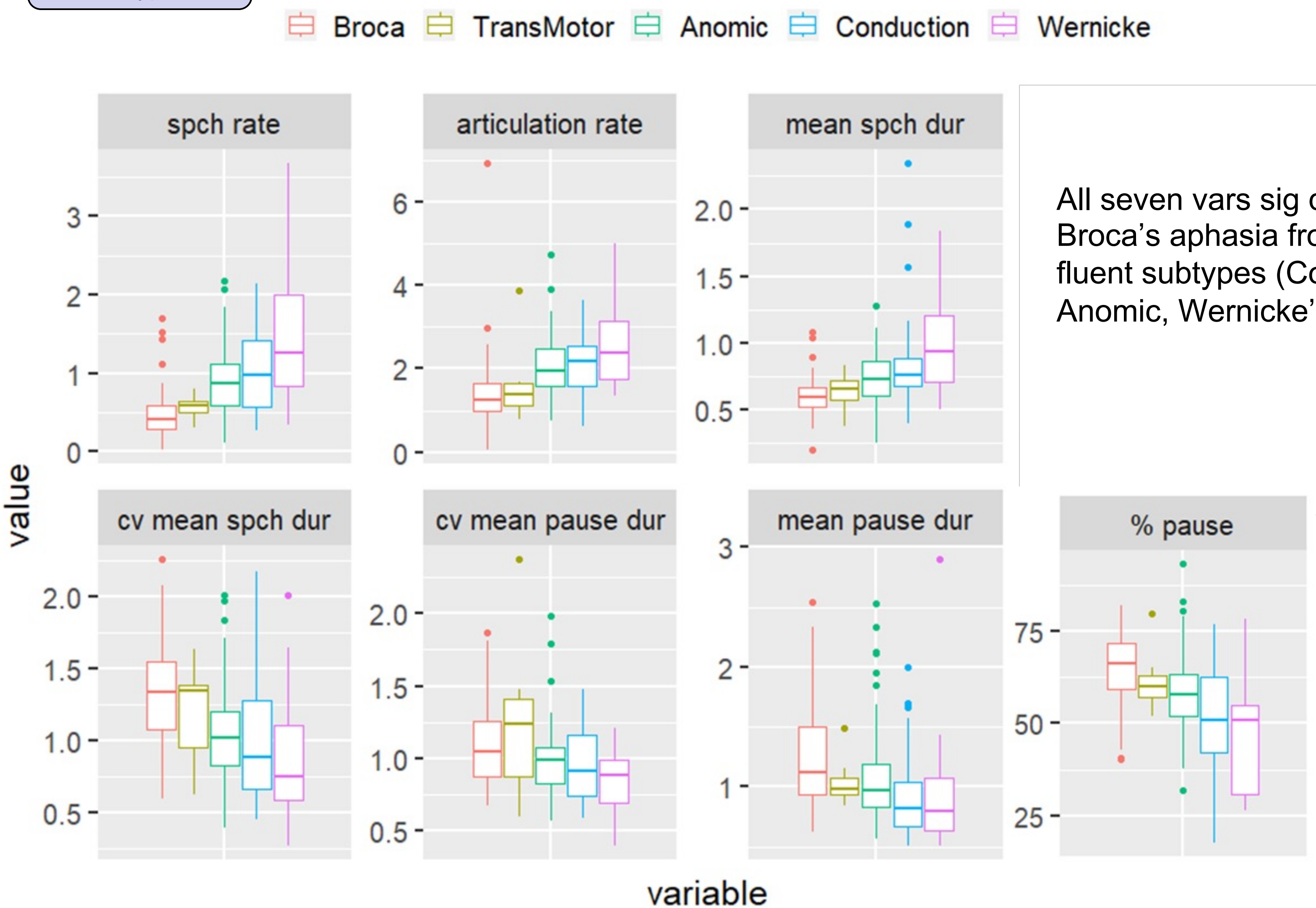
For non-fluent aphasia, sig **lower** speech rate, articulation rate, mean speech duration

Sig **higher** percent pause, speech and pause variability

No sig diff in total duration, number of pause/speech events, or mean pause duration

WAB-R aphasia subtypes

Results, Aim 1

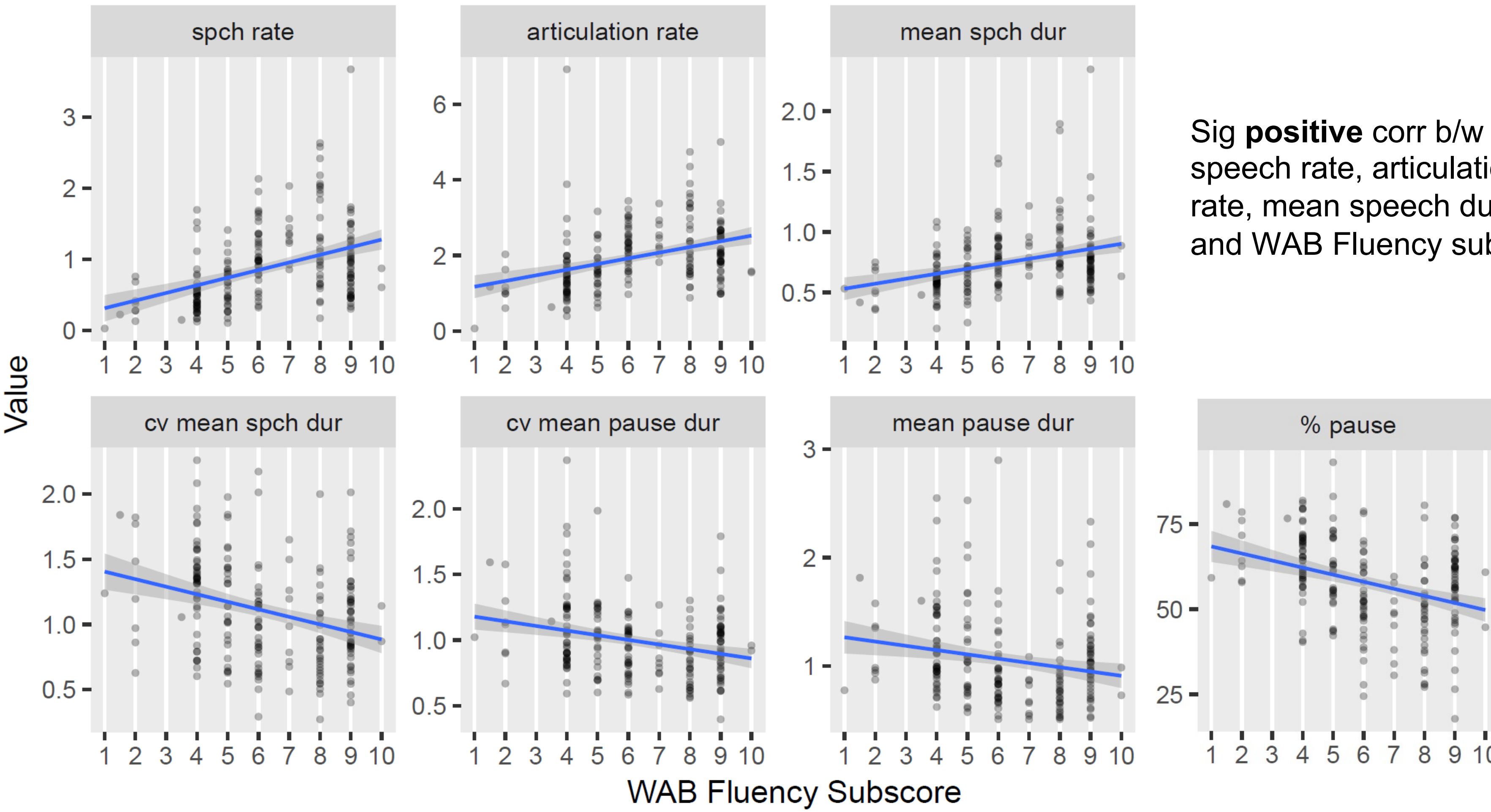


All seven vars sig differentiate Broca's aphasia from more fluent subtypes (Conduction, Anomic, Wernicke's)

Speech rate and **percent pause** show most robust differentiation across all subgroups

WAB-R Fluency subscores

Results, Aim 1

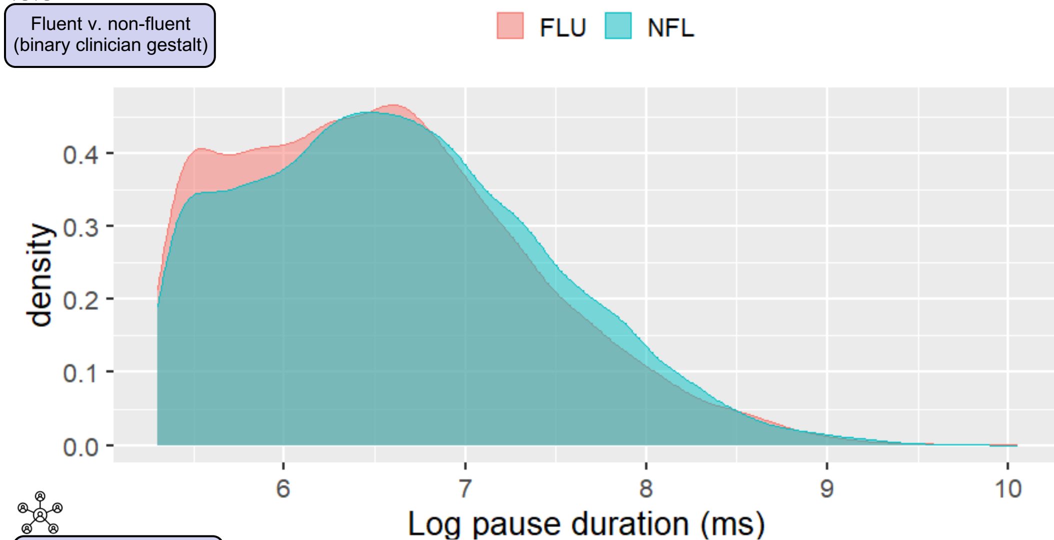


Sig **positive** corr b/w speech rate, articulation rate, mean speech duration and WAB Fluency subscore

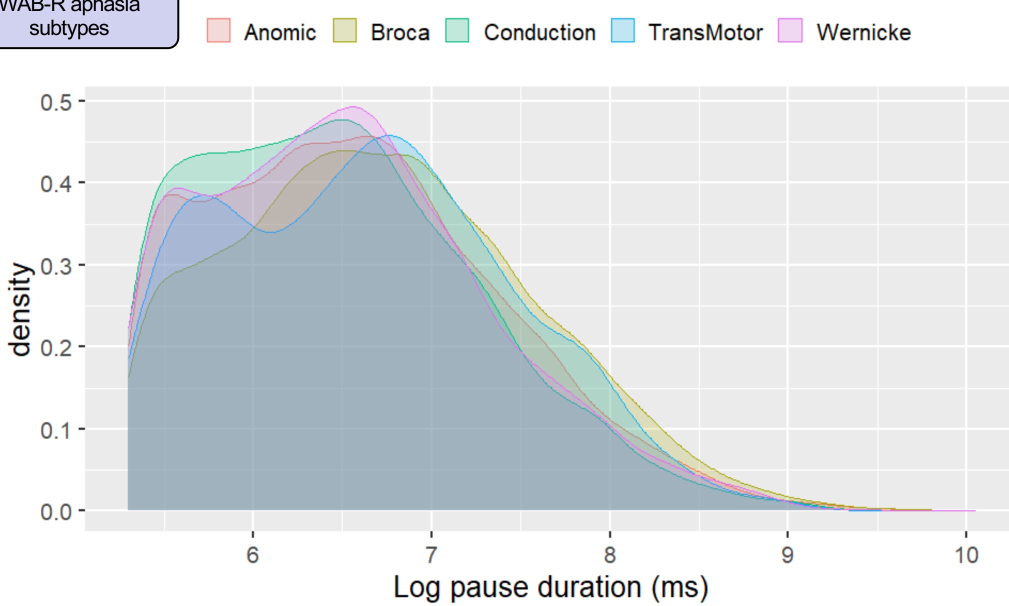
Sig **negative** corr for percent pause, variability of speech and pause duration, and mean pause duration

Results, Aim 2

Fluent v. non-fluent (binary clinician gestalt)



WAB-R aphasia subtypes



Sig **different** cumulative pause duration distributions for…

fluent v. non-fluent aphasia (p<.001)

Short and long pauses common in fluent aphasia

Long pauses more common in non-fluent aphasia

Broca's v. Wernicke's | Anomic | Conduction (p<.001)

Anomic v. Wernicke's | Conduction (p<.01)

Discussion

- Feasibility of semi-automated temporal measures to differentiate fluency profiles in post-stroke PWA
  - Overall, **important variables for differentiation were consistent** no matter which way 'fluency' was spliced
  - Joins emerging work on dx utility of temporal measures in post-stroke aphasia[1,2]

- Future direction(s) to improve clinical viability
  - Streamlining of audio processing pipeline to minimize manual labor
  - Pairing of temporal metrics with linguistic features for fuller picture of non-fluent aphasia

1. DeDe, Salis, *AJSLP* (2020)
2. Angelopoulou et al., *Neuropsychologia* (2018)

THANK YOU!

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