Diagnostic criteria for agrammatism: a critical analysis and empirical validation

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Agrammatic language production is characterized by:

- Short, grammatically ill-formed utterances with reduced syntactic complexity (e.g., Saffran et al., 1989)
  - *But*, persons with fluent aphasias (anomic, conduction) also produce syntactic errors and simplify utterances (e.g., Edwards et al., 1994)

- Errors in morphological marking, both free and bound morphemes (e.g., Miceli et al., 1989)
  - *But*, persons with fluent aphasias also produce morphological errors (e.g., Kolk & Heeschen, 1992)

- A dearth of verbs (e.g., Thompson et al., 1995)
  - *But* verb deficits are common across all aphasia types and not always tied to sentence structure deficits (e.g. Berndt et al., 1997; Matzig et al., 2009)

That is, the core features of agrammatic production are also found in non-agrammatic persons with aphasia, creating ambiguities in identifying agrammatism – <u>PROBLEM 1</u>

How is agrammatic production defined in the literature?

We analyzed peer-reviewed publications that focused on agrammatic language production (published in English, 1980 - 2017):

- A majority (65%) did not operationally define agrammatism and used proxies such as Broca's and nonfluent aphasia

- A minority (27%) provided objective language measures to document core agrammatic features

- When between-group comparisons were made to characterize agrammatism, most studies used a neurotypical comparison group, but no non-agrammatic aphasic comparison group

Thus, most existing research on agrammatic language lacks a standard definition and objective measures - <u>PROBLEM 2</u>

PURPOSE OF THIS STUDY

The overlap in core agrammatic features with other forms of aphasia (PROBLEM 1) and the inconsistent standards in defining and documenting agrammatic language (PROBLEM 2):

- Reduces the confidence with which we can delineate the unique attributes of agrammatism from the general impact of aphasia on language performance

- Hinders progress in understanding the neurolinguistic deficits underlying agrammatism

This study aimed to identify quantitative language markers in narrative language that will reliably differentiate agrammatism from non-agrammatic aphasia

METHODS

STEP 1

Participants

- 20 Neurologically Healthy controls
- 20 non-agrammatic persons with aphasia (PWA)
- 24 agrammatic PWA
- Three groups did not differ in age and education (Kruskal-Wallis test, $p>.05$)

Narrative language sample

- Aphasia bank narrative protocol was used

Analysis of narratives

- PWA were manually classified as agrammatic and non-agrammatic (Casilio et al., 2019)
- Language measures were automatically extracted (MacWhinney et al., 2011) and compared across groups (Kruskal-Wallis test) to identify those that differentiated agrammatic from non-agrammatic PWA
- Cut-off scores set as 1 standard deviation from non-agrammatic group

STEP 2

Participants

- 50 randomly selected from AphasiaBank (MacWhinney et al., 2011): 25 each Neurologically Healthy and PWA
- Classified as agrammatic or non-agrammatic using cut-off scores (from step 1) & manual rating (Casilio et al., 2019)
- Classification accuracy (% of correct classifications) was calculated by comparing against classifications obtained from manual ratings

RESULTS

Narrative measures with significant differences between agrammatic and non-agrammatic PWA

(Kruskal-Wallis test, pairwise comparisons using Dunn-Bonferroni adjustment for p-value, *=p<.05, **=p<.01, ***=p<.001)

Measure	Neurotypical Mean (SD)	Non-Agrammatic PWA Mean (SD)	Agrammatic PWA Mean (SD)	Classification Accuracy (%)
Objective Measures (MacWhinney et al., 2011)				**95.0**
MLU in morphemes	9.7 (1.4)***	6.8 (1.4)*	4.3 (2.1)	72.7
Verbs per utterance	1.6 (.2)***	1.2 (.3)*	.7 (.5)	75.0
Density	.5 (.01)***	.5 (.03)***	.4 (.07)	75.0
Noun-verb ratio	1.1 (.1)	.8 (.3)***	1.6 (.9)	72.7
Open-closed class ratio	.7 (.06)	.6 (.05)***	1 (.5)	75.0
Index of productive syntax	95.7 (6)***	89 (7)**	63.3 (18)	85.0

- Group membership was predicted with high accuracy when all six measures were considered (Logistic regression (χ^2 (6) = 16.7, p<.001, classification accuracy = 95%)
- The classification accuracy of individual measures was moderate (Table)

DISCUSSION

- This study provides a set of six measures that can be obtained from automated analyses, their cut-off scores for differential diagnosis of agrammatic aphasia, and the classification accuracy of these cut-off scores

- These measures are consistent with prior manual analyses of agrammatic narrative language (Hsu & Thompson, 2018; Rochon et al., 2000; Saffran et al., 1989; Thompson et al., 1995)

- Automated measures with cut-off scores provide benefits of time and objectivity, and will improve reliable differentiation between agrammatism and non-agrammatic a**phasia** for research and clinical purposes

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