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 – **PROBLEM 1**
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 - PROBLEM 2
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

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 1

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

STEP 2
# 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)

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

- Group membership was predicted with high accuracy when all six measures were considered (Logistic regression ($\chi^2$ (6) = 16.7, p<.001, classification accuracy = 95%)

- The classification accuracy of individual measures was moderate (Table)
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 aphasia for research and clinical purposes.
REFERENCES


