Journal Impact Factor (JIF)™ 2023: 0.2 | 5 Year JIF: 0.2 | Quartile: Q2 | *Source: JCR™ 2025 (Clarivate Analytics)*

RUPKATHA JOURNAL
ON INTERDISCIPLINARY STUDIES IN HUMANITIES

ISSN 0975-2935 | Indexed in the Web of Science Core Collection™ Emerging Sources Citation Index (ESCI)

https://doi.org/10.21659/rupkatha.v18n2.09 | Volume 18, Number 2, 2026 | Dynamic Impact Dimensions

Research article

AI as Psycholinguistic Scaffolding for Language Impairment: A Comparative Study

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Abstract

This study analyses the role of Artificial Intelligence (AI) as a scaffolding for language impairment. Drawing on psycholinguistic theories by Levelt and Dell, a comparative study of AI-generated prompts and the language of the impaired is conducted. Following a corpus-based approach, this study employs comparative and qualitative methods to analyse language components, including mean length of utterance (MLU), type-token ratio (TTR), lexical diversity, and syntactic structure. Data on the language-impaired are collected from corpora in AphasiaBank. The research examines how AI serves as support for impaired language. It also highlights the significance of AI as an auxiliary resource for experts in education, psychology, and impairment.

Keywords: Artificial Intelligence, Aphasia, Mean Length Utterance, Type-token Ratio.

Conflicts of Interest: The author/s declared no conflicts of interest.

Funding: No funding was received for this research.

Article History: Received: 14 October 2025. Revised: 08 June 2026. Accepted: 19 June 2026. First published: 26 June 2026.

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Published by: Aesthetix Media Services, India ↗

Citation: Angel, M. F. (2026). AI as Psycholinguistic Scaffolding for Language Impairment: A Comparative Study. *Rupkatha Journal,* 18(2). https://doi.org/10.21659/rupkatha.v18n2.09

1. Introduction

The growth of artificial intelligence (AI) has significantly transformed various aspects of human life. It also assists language-impaired individuals in accessing different tools and techniques. Developments in natural language processing (NLP) and machine learning have produced large language models (LLMs) capable of generating coherent, contextually appropriate, and syntactically complex text (Floridi & Chiriatti, 2020, pp. 681–694). Such advancements in technology help create resources for areas such as language impairment. These technological advancements have variously impacted domains such as education, medicine, and science, introducing new concepts, prompting a re-examination of human cognition in language. As in other fields, in psycholinguistics, where language and cognition work together, AI serves as a credible tool for creating and developing language in both impaired and non-impaired communication contexts.

Psycholinguistics, considered one of the premier areas of study in language impairment, examines how humans acquire, produce, comprehend, and represent language in the mind. Various theoretical frameworks in psycholinguistics are applied to the area of language impairments. One of the acquired language impairments, Aphasia, usually caused by stroke or brain injury, disrupts the processes of lexical retrieval, syntactic encoding, and discourse-level organisation, resulting in fragmented, telegraphic, or semantically incomplete speech (Goodglass & Kaplan, 1983, pp.1-30). It appears either immediately after the injury or as a degenerative condition. To conduct studies on disoriented language and its comparison with normal language production, researchers have long relied on aphasia corpora, such as AphasiaBank (MacWhinney et al., 2011). Cross-linguistic and cross-population comparative studies also need examination of different corpora.

Vygotsky's theory of scaffolding, later expanded by Wood, Bruner, and Rose (1976), posits scaffolding as an organised support that could be removed slowly as the learners advance. The role of AI is a supporting resource. Rather than being a therapeutic agent, AI is seen as a diagnostic and analytical tool that helps us understand language processes and their use in inclusive communication (Bender & Koller, 2020). Large language models do not truly understand or think; they mimic the patterns of human language with impressive fluency (Bender, E. M., & Koller, A, 2020). This study is an intersection of both psycholinguistic and corpus-based methods to analyse language impairment, focusing on how AI-generated responses might assist. The paper does not aim to picture Ai as a therapy, but to explore how its output can assist diagnosis, theory, and language analysis for sentence-level disorders and word-finding problems. This research offers a practical way to study impaired language using modern technology. Voyant Tools, a web-based application providing interactive visualisations of word frequency, keyword trends, and co-occurrence patterns (Sinclair & Rockwell, 2016), was utilised for data analysis. The findings are expected to inform frameworks in digital and health humanities and support the development of systems in language studies. language studies.

The study, in addition to contributing to the research, highlights social responsibility by aligning with the United Nations Sustainable Development Goals, including Good Health and Well-being (SDG 3), Quality Education (SDG 4), and Reduced Inequalities (SDG 10). It also provides therapists and educators with concepts to maintain the interdisciplinary nature by implementing more effective rehabilitation techniques and developing inclusive learning interventions. By integrating psycholinguistic theory with AI-generated language, the research demonstrates the role of technology in advancing accessibility, inclusivity, and understanding of language processes (Chowdhury, 2003; Floridi & Chiriatti, 2020, pp.681–694). AI is redefining the field of language study.

This research, by analysing lexical diversity, syntactic complexity, function-word usage, and mean length of utterance in language production, proves that AI-generated language will serve as a linguistic scaffold for analysing Aphasic language impairment.

2. Review of literature

Psycholinguistic studies play a major role in language impairment research through different perspectives on how language is constructed, processed, and produced in the human brain. Aphasia has been a subject of psycholinguistic study for a long time. Among the various types of aphasia, agrammatism—often associated with Broca's aphasia—is characterised by simplified syntax, omission of function words, and reduced sentence complexity (Goodglass & Kaplan, 1983). Both clinical observation and pure linguistic analysis have been carried out in this research. These studies have also focused on the significance of sentence production in impaired language and have created models.

This particular research is grounded in two theoretical frameworks. Firstly, the Spreading Activation Model by Dell (1986) demonstrates errors in lexical retrieval. Secondly, Levelt's model of speech production (1989) provides a structured explanation of how utterance planning is carried out, which makes it inevitably relevant for identifying issues in the impaired language.

The role of corpus linguistics in contributing to the field of language impairments is significant in recent years. AphasiaBank is a corpus that provides annotated datasets of spontaneous speech from individuals with different aphasia types, helping identify linguistic patterns across populations (MacWhinney et al., 2011). Voyant Tools by quantifying lexical diversity, syntactic frequency, and other linguistic variables play crucial role in applied linguistics and clinical linguistics, (Yu, 2009)

A study conducted by Mao, L., Lee, J. H., Shah, Y. F., & Valencia, S. (2025), titled Design Probes for AI-Driven AAC: Addressing Complex Communication Needs in Aphasia, studies how AI platforms enhance the augmentative and alternative communication tools for people with Aphasia by following a design-based methodology. To assist with human communication needs, the researcher sought to demonstrate that AI is a communicative partner rather than merely a technical advancement. In light of communication needs, the researchers presented AI tools as a communicative partner rather than merely a technical advancement.

Van Vaals, S., Matusevych, Y., & Tsiwah, F. (2024) conducted a study titled Generating Completions for Fragmented Broca's Aphasic Sentences Using Large Language Models which investigates how large language models, such as GPT, can act as a complement in telegraphic and fragmented speech, which is an outcome of Aphasia.

Another study by Zhong, X. (2024), titled AI-Assisted Assessment and Treatment of Aphasia: A Review, discusses how AI technologies can be applied to therapeutic intervention for Aphasia. This study also reviews AI models' ability to analyse large datasets.

Leveraging Pre-trained Large Language Models for Aphasia Detection in English and Chinese Speakers is another study by Cong, Y., Lee, J., & LaCroix, A. (2024), which defines the use of AI language models for detecting English and Chinese. Here, the researcher trained the AI model to identify linguistic markers of Aphasia, such as deficits in fluency and lexical repetition.

3. Research Objectives

This study researches the following objectives;

- Using the corpus-based approach, quantitatively analyse the language production of aphasic patients, especially identifying the sentence structure, lexical diversity (TTR), and syntactic complexity patterns in narrative production tasks.
- To find out the Mean Length Utterance (MLU), function word usage, and lexical diversity metrics between the speech samples of aphasia and AI-generated language responses.
- To identify if the AI-generated responses can be used as a linguistic benchmark by studying fluent, grammatically intact language production.
- To evaluate the theoretical possibility of AI-generated language as a framework for assessing the specific linguistic deficits in aphasic speech.

4. Methodology

4.1 Research Design

This research is grounded in a corpus-based approach with a focus on comparative and qualitative approaches. The study focuses on analysing and comparing language samples of Aphasic individuals. 15 samples were chosen for the study. Small-to-moderate sample sizes are common and defensible in corpus-based and case-oriented psycholinguistic research when the design prioritises depth, reproducibility, and paired within-case contrasts (Yin, 2014; Guest, Bunce, & Johnson, 2006). The data were collected from the existing corpus (AphasiaBank) and from AI-generated language generated by the AI tool ChatGPT. Corpus linguistics allows for the systematic quantification of language impairments, offering objective insights into lexical and syntactic deficits in aphasic speech (Armstrong, 2005a, pp.137-153). The language elements analysed in the study are sentence construction, lexical richness, and syntactic complexity, to determine whether AI can serve as a linguistic scaffold.

4.2 Human Language Data

The primary data for the study are drawn from the AphasiaBank corpus. It is a publicly accessible, peer-reviewed database of transcribed speech samples from individuals with various types of Aphasia. The primary dataset for impaired language is sourced from AphasiaBank; 15 samples related to narrative or descriptive tasks, such as Cinderella Story Retelling and picture description, were selected and studied. The exploratory nature of this research, along with the need to build a concept within the constraints of corpus access, guided the restriction of the sample to 15. Small-to-moderate sample sizes are common and defensible in corpus- and case-oriented psycholinguistic research when the design prioritises depth, reproducibility, and paired within-case contrasts (Yin, 2014; Guest, Bunce, & Johnson, 2006,pp.59-82). To find out the systematic structural difference, a paired design, pairing the transcript with an AI-generated response, gives generated response, gives a strong foundation.

4.3 AI-Generated Data:

The research collected responses to the same prompts used in the AphasiaBank. using the AI tool ChatGPT, to ensure the comparability of the human, length, tone, and content expectations of the human speech.

4.4 Research Tools for Analysis.

This research has used two tools. The details are as follows;

- Voyant Tools: This is a web-based text analysis tool used to visualize word frequency, sentence length, and linguistic trends.
- ChatGPT: ChatGPT is an AI tool that is a chatbot developed by OpenAI, utilising a large language model to respond to prompts.

5. Analysis and Interpretation

Below is the detailed analysis of the data: AI-generated narrative production and aphasic patients' data.

This corpus contains 15 documents with 1,283 total words and 317 unique word forms.					
Document Length:					
Longest:	AI_Cinderella_01 (119)	AI_Cinderella_02 (119)	AI_Cinderella_03 (106)	AI_Cinderella_04 (105)	AI_Cinderella_05 (97)
Shortest:	AI_Cinderella_13 (67)	AI_Cinderella_15 (68)	AI_Cinderella_14 (68)	AI_Cinderella_10 (72)	AI_Cinderella_11 (73)
Vocabulary Density:					
Highest:	AI_Cinderella_08 (0.776)	AI_Cinderella_15 (0.750)	AI_Cinderella_12 (0.747)	AI_Cinderella_13 (0.746)	AI_Cinderella_04 (0.743)

Lowest:	AI_Cinderella_02 (0.655)	AI_Cinderella_01 (0.681)	AI_Cinderella_14 (0.691)	AI_Cinderella_09 (0.693)	AI_Cinderella_06 (0.695)
Average Words Per Sentence:					
Highest:	AI_Cinderella_02 (13.2)	AI_Cinderella_10 (12.0)	AI_Cinderella_01 (11.9)	AI_Cinderella_03 (11.8)	AI_Cinderella_06 (11.7)
Lowest:	AI_Cinderella_15 (9.7)	AI_Cinderella_11 (10.4)	AI_Cinderella_09 (10.7)	AI_Cinderella_12 (10.7)	AI_Cinderella_05 (10.8)
Readability Index:					
Highest:	AI_Cinderella_06 (10.858)	AI_Cinderella_10 (10.725)	AI_Cinderella_04 (10.699)	AI_Cinderella_07 (10.026)	AI_Cinderella_08 (9.868)
Lowest:	AI_Cinderella_09 (8.564)	AI_Cinderella_01 (8.741)	AI_Cinderella_11 (8.748)	AI_Cinderella_03 (9.034)	AI_Cinderella_02 (9.088)
Most frequent words in the corpus:					
prince (32)	slipper (27)	cinderella (26)	ball (21)	fit (14)	
Distinctive words (compared to the rest of the corpus):					
AI_Cinderella_01:	warned (1)	trying (1)	stroke (1)	pumpkin (1)	mice (1).
AI_Cinderella_02:	wept (1)	sparkling (1)	sleep (1)	scrub (1)	remarried (1).
AI_Cinderella_03:	shabby (1)	rode (1)	ragged (1)	house (1)	eyes (1).
AI_Cinderella_04:	vain (1)	tyranny (1)	spell (1)	granted (1)	forever (1).
AI_Cinderella_05:	turning (1)	torn (1)	sending (1)	selfish (1)	knew (1).
AI_Cinderella_06:	washed (1)	obedient (1)	luxury (1)	joyfully (1)	home (1).

AI_Cinderella_07:	used (1)	tested (1)	send (1)	queen (1)	father's (1).
AI_Cinderella_08:	came (2)	shone (1)	providing (1)	placed (1)	perfectly (1).
AI_Cinderella_09:	vowed (1)	tasks (1)	ran (1)	mistreated (1)	met (1).
AI_Cinderella_10:	sweeping (1)	stepmother's (1)	scrubbing (1)	orders (1)	lifted (1).
AI_Cinderella_11:	weeping (1)	unkind (1)	trapped (1)	surprised (1)	sisters (1).
AI_Cinderella_12:	wed (1)	tale (1)	splendor (1)	sent (1)	poorly (1).
AI_Cinderella_13:	world (1)	riches (1)	remained (1)	pure (1)	journeyed (1).
AI_Cinderella_14:	shining (1)	miracle (1)	later (1)	hurriedly (1)	freed (1).
AI_Cinderella_15:	smitten (1)	oppressed (1)	news (1)	godmother's (1)	faithfully (1).

Table 1: AI-Generated Language Corpus Metrics

This table shows the consistent language production quality of the Aphasic subjects. This corpus contains remarkable, lexically rich, syntactically complex, and thematically grounded language production, totalling 1,283 words and 317 unique word forms. The type-token ratio is promising and shows a strong lexical diversity in the AI-generated content. Key observations from this data are that the vocabulary Ranges from 0.655 - 0.776, with 60% of samples achieving >0.70 density. This shows an efficient lexical selection by subjects. There is no redundancy. Sentences are presented with appropriate clause structures, coordination, and a strong syntactic base; the average word quantity per sentence is 9.7-13.2. The narrative features are sophisticated with a moderate complexity score of 8.564-10.858, which will help in comparative analysis. According to the table data, the high-frequency words are prince, slipper, Cinderella, and ball, which reflect the thematic coherence and unity in narration across the samples. This analysis would provide a baseline to consider AI-generated text as a framework for comprehensive language production.

This corpus contains 15 documents with 3,845 total words and 495 unique word forms.					
Document Length:					
Longest:	### Patient 15 (1102)	### Patient 11 (651)	### Patient 13 (412)	### Patient 12 (403)	### Patient 9 (351)
Shortest:	### Patient 6 (12)	### Patient 3 (17)	### Patient 1 (70)	### Patient 8 (73)	### Patient 7 (73)
Vocabulary Density:					
Highest:	### Patient 3 (0.882)	### Patient 2 (0.675)	### Patient 1 (0.629)	### Patient 5 (0.497)	### Patient 4 (0.493)
Lowest:	### Patient 15 (0.195)	### Patient 8 (0.233)	### Patient 7 (0.233)	### Patient 9 (0.282)	### Patient 11 (0.283)

Average Words Per Sentence:					
Highest:	### Patient 13 (206.0)	### Patient 12 (201.5)	### Patient 15 (78.7)	### Patient 11 (40.7)	### Patient 14 (35.3)
Lowest:	### Patient 3 (4.3)	### Patient 6 (6.0)	### Patient 1 (7.0)	### Patient 2 (8.2)	### Patient 4 (9.3)
Readability Index:					
Highest:	### Patient 5 (6.277)	### Patient 2 (4.953)	### Patient 13 (4.175)	### Patient 11 (4.147)	### Patient 4 (3.794)
Lowest:	### Patient 6 (-3.550)	### Patient 8 (-0.727)	### Patient 7 (-0.450)	### Patient 9 (-0.109)	### Patient 3 (0.271)
Most frequent words in the corpus:					
uh (282)	um (98)	cinderella (39)	oh (36)	know (30)	
Distinctive words (compared to the rest of the corpus):					
### Patient 1:	dance (3)	wearing (1)	sure (1)	supposed (1)	stepchildren (1).
### Patient 10:	know (9)	uh (11)	carriage (2)	called (2)	okay (6).
### Patient 11:	woman (9)	uh (33)	party (6)	man (7)	she's (4).
### Patient 12:	uh (67)	everybody (4)	able (4)	outside (3)	try (2).
### Patient 13:	um (56)	slipper (4)	father (3)	know (6)	coach (2).
### Patient 14:	monster (4)	good (4)	end (3)	right (2)	mom (2).
### Patient 15:	uh (46)	old (7)	said (10)	gotta (5)	mother (8).
### Patient 2:	return (2)	slipper (2)	glass (2)	women (1)	used (1).
### Patient 3:	happily (1)	met (1)	lived (1)	got (1)	went (1).
### Patient 4:	stepsisters (5)	home (2)	tried (2)	father (2)	key (1).
### Patient 5:	stepsisters (5)	nasty (2)	home (2)	helped (2)	brought (2).
### Patient 6:	www (1)	know (1).			
### Patient 7:	yes (12)	uh (21)	oh (10)	okay (6)	shoot (2).
### Patient 8:	yes (12)	uh (21)	oh (10)	okay (6)	shoot (2).
### Patient 9:	uh (76)	cousins (6)	sudden (7)	better (4)	search (3).

Table 2: Aphasic patient Corpus Metrics

The corpus shows significant variability in the language production of the aphasic patients, comprising 3845 words and 495 unique word forms across 15 documents. This shows that, compared with AI-generated data, it produces verbose, repetitive, and effortful language. The analysis shows that there is a difference in verbal output capacity among patients. With 40% of patients scoring below 0.3, it suggests wide lexical access impairment with a density score of 0.195-0.882. The average words per sentence range from 40.3 to 206.0, which is evidence of distracted syntactic planning, and some of them manage only telegraphic speech. The frequency of hesitation markers such as “uh”, “um”, and “oh” is high, which dominates the corpus, a discourse a discourse strategy for word finding.

This word analysis reveals patient-specific lexical strategies and semantic field restrictions, with a more distributed distribution of very limited thematic vocabulary development over basic narrative elements.

Figure 1: Word cloud of AI-generated data

The AI word cloud showcases a clear lexical arrangement across narrative elements. The thematic focus is appropriately distributed throughout the speech by producing words such as “Cinderella”, “Prince”, “godmother”, and “slipper”. Equally proportionate representation of supporting vocabulary is also given in the word cloud (“midnight,” “stepmother,” “palace,” “magical”). Both reflect the ideal semantic field of activation in the data. The efficient lexical selection with profound grammatical encoding aligns with Levelt’s Speech Production Model.

Figure 2: Word cloud of Aphasic patients

The predominance of hesitation markers and discourse fillers is visualised in the word cloud of n=15 patients. It illustrates the agrammatic linguistic profile of aphasic patients. The prominence of the filler "uh" (n=282) cover 7.3 % corpus, and "um" (n=98) covers 2.5 % of the corpus. It shows that the aphasic patient's speech with thematic or propositional content has been replaced by fillers. The splintered lexical choice is evident in the content words ("prince", "ball", "okay"), and the prominence of "Cinderella" indicates the restricted semantic knowledge. This leads to the conclusion that the non-fluent nature of agrammatic speech production is vigorous in aphasic speech. As Dell's spreading activation theory predicts, restricted lexical networks result in compensatory verbal behaviours.

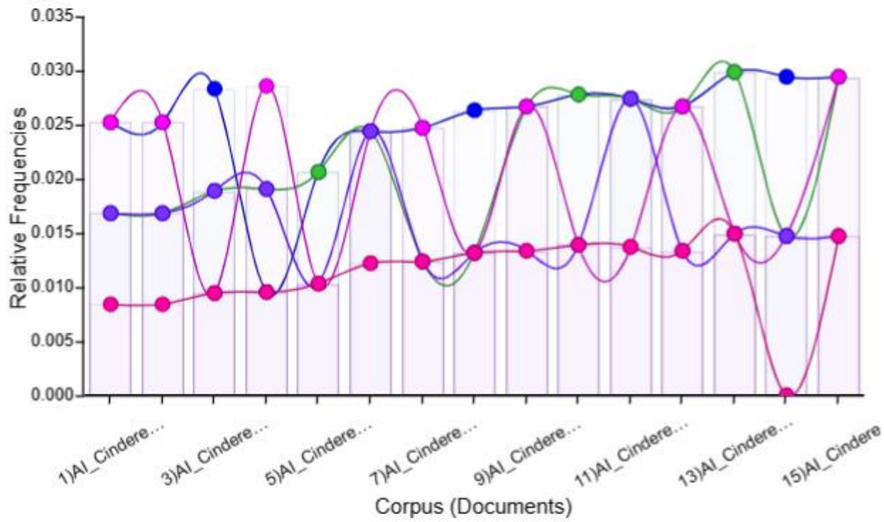

Figure 3: AI-generated language sample frequency graph

The graph shows consistent lexical distribution and stable vocabulary use across all 15 samples. The overlapping trend lines show relative frequency, which is stable across key narrative elements with minimal variance between samples. The steady frequency of core vocabulary shows lexical stability. Consistency in narrative elements shows thematic coherence in the content. Stable word distribution patterns are underlying grammatical structures.

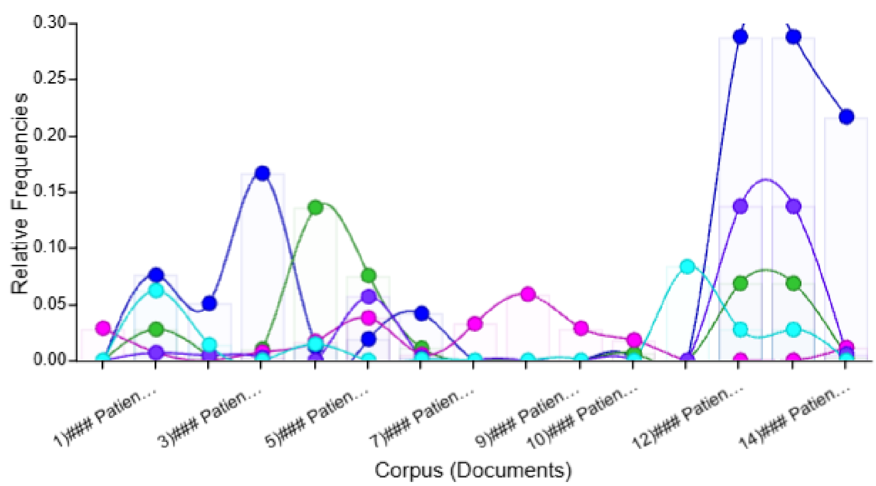

Figure 4: Aphasic language sample frequency graph

Aphasic patients exhibit extreme interpatient variability and disordered consistency in lexical patterns during narrative production. Patient 12-15 shows extreme frequency spikes corresponding to stereotyped responses. There is no anchored frequency foundation across the patients. As evidence for individualised breakdown profiles, each patient presents unique frequency patterns.

5.1 Quantitative Corpus outline

Findings from the Voyant Tool analysis indicate a marked linguistic disparity between the AI-generated corpus and the corpus of aphasic patients. Though the word count in the aphasic corpora is relatively high, it shows the yielding type-token ratio (TTR). TTR for AI corpora is 0.247, whereas it is 0.129 for Aphasic corpora. The higher the TTR, the higher the lexical diversity and efficiency. This shows the repetition of words and the use of compensatory strategies such as hesitation markers, such as "uh" (282 times), "um" (98times). The patients use the trial-and-error method for self-correction. This finding aligns with Dell's Spreading Activation Theory, in which lexical access networks in aphasia exhibit controlled activation patterns compared with those of AI systems. Considering objective 1 of this study, the speech patterns of aphasia show profound syntactic and morphological impairments, which are consistent with agrammatic aphasia profiles. The MLU value ranges from 1.7 to 2.6 among patients with M=2.13 and SD=0.28. It shows a discrepancy in word production compared with the normative adult value of 12-15 words per utterance. As in Levelt's (1989) speech production model, it identifies disruptions in the phase of grammatical encoding and how they break down in the system. With a corpus mean of 0.329, the TTR varies considerably, ranging from 0.195 to 0.882. When there is an extreme variation, it reveals the range of linguistic deficits rather than uniformity. Some patients' TTR scores, such as patients 15, 8, and 7, range from 0.195 to 0.233, with filler words and hesitation markers showing the highest frequency, indicating compensatory strategies for word-finding troubles.

Furthermore, the corpus contains approximately 10.7% paralinguistic features, representing a significant proportion of the verbal output. This verbal output is a compensatory mechanism rather than the propositional content. This finding supports Thompson and Shapiro's (2007). The characterisation of agrammatic speech as marked by effortful, non-fluent production with frequent disruptions in syntactic planning. Considering the second objective of the study, the primary lexical item in the content word analysis is "Cinderella" (n=39), followed by "know" (n=30), indicating restriction in semantic knowledge and syntactic-semantic knowledge of the narrative. Grammatical morphemes are not present in the speech. This confirms the lack of usage of complex function words and conjunctive components in high-frequency positions.

Comparing AI vs Aphasic language production, the study concludes that semantically sophisticated content words' frequency is higher in AI-generated content: "prince" (n=32, 2.5%), "slipper" (n=27, 2.1%), "Cinderella" (n=26, 2.0%), and "ball" (n=21, 1.6%). This placement reflects a narrative structure that is coherent and appropriate to the thematic vocabulary. Lexical selection is efficient without redundancy. In contrast, the aphasic corpus shows an insolvent nature of semantic content and thematic vocabulary. Another observation is in the number of words per sentence. AI samples range from 9.7 to 13.2 words per sentence (M = 11.6), suggesting complex clause structure and coordination. The values of readability indices (8.564-10.858) suggest the syntactic constructions which are suitable for narrative discourse. Aphasic samples exhibit severely diminished sentence structure, with most patients producing telegraphic utterances. The wide range in average words per sentence (4.3-206.0) reflects the heterogeneous nature of aphasic production, with some patients producing occasional, lengthy, but poorly structured utterances, while others maintain consistently minimal output.

The study opens a unique window into a framework of language production. AI-generated responses serve as an idealised production model, preserving fluency, lexical richness, and syntactic diversity, which can be charted against aphasic deficits to determine disintegration in language production. This word analysis shows AI's ability to vary its lexical choices and context, which fits. Terms like "shabby," "tyranny," "luxury," and "joyfully" illustrate semantic rigour, which would be restorative for individuals with a deficiency in word production.

5.2 Clinical Applications and diagnostic framewroks

This study reflects several clinically significant patterns:

- The large proportion of hesitation markers, 10.7 % gives a benchmark for identifying deficits in fluency and identifying therapeutic methods.
- •Values of TTR below 0.3 suggest prospective utility for diagnosis for measuring the severity of aphasia
- A syntactic framework can be generated for therapeutic intervention, offering models for the hierarchical sentence structures speakers struggle to produce.

While learning about the methodological innovations and future directions of this study, it moves beyond quantitative, corpus-based linguistic comparative analysis in aphasia research and beyond clinical diagnosis. The study can contribute to a standardised comparison derived from consistent, fluent responses to the narrative prompts. Corpus tools enable analysis of large datasets using traditional manual coding methods. The comparative study also includes components of Levelt's speech production model, which discusses speech breakdown in aphasia. Through the study, the phenomenon of linguistic mirroring is revealed. And this approach opens new directions for diagnosis and intervention design.

6. Discussion

By offering both theoretical and practical insights, this corpus-based comparative study provides evidence for using AI-generated language production as a scaffold for understanding aphasic speech patterns more generally. The findings show salient differences in language production and language patterns of impaired language. The drastic differences between linguistic elements in both aphasic and AI-generated language provide experimental and empirical evidence for theories of speech production. Levelt's speech production model (1989) is exclusively about the grammatical encoding disruptions regarded as the breakdown of what he mentions in his theory.

Similarly, supported by Dell's proposition theory, aphasia involves weakened connections in lexical networks, resulting in reduced activation spread and, consequently, limited vocabulary access. The hesitation markers in novel quantitative evidence for compensatory mechanisms in language production. This finding identifies a new compensatory mechanism in narrative language production. It creates a novel method beyond clinical observations and leads to a breakdown of linguistic signals.

The importance of using a corpus-based approach in clinical language research is relevant in the arena of language research. Combining systematic quantification with the Voyant Tool strengthens traditional methods of analysis. Provided, a potential application to the field of medical humanities and clinical studies, it creates an established framework for linguistics studies in collaboration with artificial intelligence. As a future implication, the study can be extended to a larger population, but it should be studied with a standardised assessment tool. Additionally, the study takes a cross-linguistic and cultural approach to examine whether the narrative structures follow the same pattern across various cultures and linguistic settings. There are several limitations for this study. The sample is size is insufficient to draw authentic conclusions statistically though it is appropriate for a pilot corpus-study. Furthur studies are necessary to support the statistical conclusions. The scope for extending this study to other discourse type is present along with the component of narrative language production. It also allows for blending the fields of computational linguistics, clinical psychology, and artificial intelligence. Keeping this study as a base, further stidies on dementia, traumatic brain injuries, and developmental language disorders can be conducted.

7. Conclusion

From the objective, it is concluded that broken-down speech patterns require psycholinguistic scaffolding to examine AI-generated language. This corpus-based comparative analysis reveals quantifiable disparities in language components, such as lexical diversity, syntactic complexity, and production efficiency, which align with theories of speech production and language impairment. While AI models cannot replicate the cognitive complexity of human language production, they can serve as a functional model for linguistic output, designating specific areas of deficits in the neurologically impaired population. As mentioned in the discussion, future research should extend the methodology to extended populations of both clinical and educational settings to provide additional insights. This study establishes a novel framework for aphasia research that leverages artificial intelligence not as a replacement for clinical assessment, but as a sophisticated tool for determining the convolution of human language production. The evidence provided here opens the way to continue to explore the field in much more detail.

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