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Non-fluent speech following stroke is caused by impaired efference copy

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Abstract

Efference copy is a cognitive mechanism argued to be critical for initiating and monitoring speech: however, the extent to which breakdown of efference copy mechanisms impact speech production is unclear. This study examined the best mechanistic predictors of non-fluent speech among 88 stroke survivors. Objective speech fluency measures were subjected to a principal component analysis (PCA). The primary PCA factor was then entered into a multiple stepwise linear regression analysis as the dependent variable, with a set of independent mechanistic variables. Participants' ability to mimic audio-visual speech ("speech entrainment response") was the best independent predictor of non-fluent speech. We suggest that this "speech entrainment" factor reflects integrity of internal monitoring (i.e., efference copy) of speech production, which affects speech initiation and maintenance. Results support models of normal speech production and suggest that therapy focused on speech initiation and maintenance may improve speech fluency for individuals with chronic non-fluent aphasia post stroke.

Keywords

Aphasia; efference copy; speec	ch entrainment; speech fluency; stroke	

Introduction

Contemporary models of speech production suggest that an internal representation of the speech plan, known as an efference copy, predicts speech behaviour (Guenther, Ghosh, & Tourville, 2006; Hickok, Houde, & Rong, 2011; Hickok, 2015; Hickok & Poeppel, 2007; Houde & Chang, 2015; Houde & Nagarajan, 2011). An efference copy is a replica of the

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speech motor plan and is hypothesized to generate forward predictions of auditory targets to be compared to actual feedback during speech execution (Guenther et al., 2006; Hickok, 2015; Hickok et al., 2011). Although models of speech production differ with regard to the precise nature of efference copies, feedforward and auditory feedback control mechanisms including efference copies have long been acknowledged to be crucial for the initiation and monitoring required for fluent speech (Guenther, 2016). In this paper, we investigate the extent to which breakdown of efference copy mechanisms may account for non-fluent speech in stroke survivors.

The directions into the velocities of the articulators (DIVA) model of speech production describes interacting feedforward and feedback control systems for speech motor control (Guenther, Hampson, & Johnson, 1998). According to this model, an efference copy, consisting of a set of feedforward motor commands that project from motor regions, carries internal auditory target information to the posterior auditory cortex, predicting auditory consequences of the spoken message (Guenther et al., 2006; Guenther et al., 1998). If an incoming auditory signal is outside the parameters of the predicted auditory target, then corrective motor plans are generated to remedy the perceived discrepancy between the actual and projected targets. If feedforward projections to primary motor cortex (i.e., from a speech sound map to an articulator map) are damaged, this probably impacts programming required for speech, because the appropriate motor commands cannot be accessed. However, such damage may also impair feedback control, because feedforward projections carry sensory targets for speech sounds (relayed from ventral premotor cortex to higher order auditory and somatosensory brain regions). Without these sensory targets, errors in initiation or actual production cannot be detected via auditory or somatosensory feedback, thus eliminating sensory feedback-based corrective motor commands (Guenther, 2016). Consistent with the DIVA model, research has shown that speech production is dependent on real-time auditory and proprioceptive feedback (e.g., Guenther, 2006).

State feedback control (SFC) models also integrate efference copies by means of feedforward and feedback control mechanisms (Hickok, 2012; Hickok et al., 2011; see also Houde & Nagarajan, 2011; Tian & Poeppel, 2010). According to SFC models, phonological-level representations are separated into internal motor targets and auditory consequences. Speech acts initiate a motor speech plan and an exact efference copy of that plan providing sensory targets at the level of proprioception and audition. Online sensory feedback control is attributed to efference copy, as well as an internally maintained representation of estimates of the current dynamical vocal tract state (Hickok et al., 2011). More recently, efference copies have been proposed to be part of planning a speech motor act prior to execution, rather than after the initiation of a motor command (Hickok, 2015). Similar to the DIVA model, SFC models imply that problems with efference mechanisms would be likely to impact naturally occurring feedforward and feedback processes required for the initiation and monitoring of speech production. Both DIVA and SFC models consider efference copies to be important for fluent speech production, and therefore these and other similar models of speech production do not necessarily conflict with one another in this respect.

The DIVA and SFC models of speech production are broadly consistent with classic neurocognitive models of language that include auditory—motor integration (e.g.,

Geschwind, 1979; Lichtheim, 1885; Wernicke, 1874) as well as with early psycholinguistic models of language production (e.g., Dell, Schwartz, Martin, Saffran, & Gagnon, 1997; Levelt, Roelofs, & Meyer, 1999). For example, Levelt et al.'s (1999) process of phonetic encoding yields a gestural score that is subsequently executed by the articulatory mechanism, analogous to feedforward control. Additionally, self-repairs during spontaneous speech provide evidence of an internal mechanistic process. Levelt (1989) attributed immediate corrections of erroneous initial syllables of a word to the phonetic plan ("internal speech"), but did not offer insight regarding a mechanism responsible to detect errors prior to speech production. Additionally, an internal monitor of the phonological plan, which relies on the same mechanism as that for external monitoring of articulated speech, has been postulated (Levelt et al., 1999). Hickok (2015) suggests that repeated attempts to correct for phonemic speech errors are due to mismatches between the efference copy and the actual sensory feedback, as evidenced by studies from the aphasia literature (e.g., Baldo, Klostermann, & Dronkers, 2008; Goodglass, 1992).

As discussed above, efference copy is a cognitive mechanism argued to be crucially important for initiating and monitoring speech. Recent evidence suggests that the generation of efference speech copies relies on the left inferior frontal gyrus (e.g., Niziolek, Nagarajan, & Houde, 2013; Wang et al., 2014) and that structures at the parietal-temporal junction serve to integrate sensorimotor transformations (Hickok, 2015). Thus, damage to these regions would impair one's ability to generate and use an efference copy for speech motor control. If fluent speech relies on each motor action to be initiated by a motor plan with simultaneous generation of an internal copy against which the sensorimotor consequences can be compared in real time, then individuals without the ability to generate or access an efference copy would produce less fluent speech (Fridriksson, Basilakos, Hickok, Bonilha, & Rorden, 2015; Fridriksson et al., 2012).

One way to clarify to what extent breakdown of efference copy mechanisms impact speech fluency is by studying individuals with focal neurological damage, including stroke survivors. Investigating speech fluency in stroke survivors with or without damage to left inferior frontal gyrus and temporoparietal junction may elucidate a mechanism such as efference copy, responsible for speech fluency. Non-fluent speech is one of the most salient and troublesome symptoms of Broca's aphasia, an acquired language disorder affecting at least 20% of chronic stroke survivors (Engelter et al., 2006). Non-fluent speech production is characterized by short, interrupted utterances that are articulated with effort and abnormal prosody, and may be grammatically incorrect. In contrast, fluent speech is characterized by long, uninterrupted, and often grammatical or paragrammatic strings of different words that are articulated without effort. These speech production characteristics vary in expression and independence along a severity continuum (Goodglass, 1993). Accordingly, many speech production features contribute to perceptions of speech fluency (Gordon, 1998; Park et al., 2011). Therefore, the idea of efference copy as a primary cognitive mechanism responsible for the flow of speech has important clinical and theoretical implications. For example, determining the cognitive mechanisms accountable for non-fluent speech is important to guide assessment and therapeutic strategies targeting impaired speech fluency. In this manner, results may also inform neural models of normal speech production.

It must be noted that speech fluency is a multidimensional construct with many speech production features contributing to the perceptions of speech fluency (Gordon, 1998; Park et al., 2011). Evaluation of speech fluency therefore requires consideration of several aspects of speech production. The Western Aphasia Battery (WAB; Kertesz, 1982, 2007) is one of the most frequently used tests to identify the presence and type of aphasia in neurological populations. The WAB includes several sub-tests, including a qualitative rating scale that can be used to evaluate speech fluency based on a spontaneous speech sample and verbal picture description. According to the WAB manual, speech-language pathologists (SLPs) subjectively rate speech fluency based on perceptual impressions of sentence length and complexity, rate of speech, and the presence of paraphasias. Despite its widespread use in research and clinical settings, fluency scores obtained from the WAB do not provide specific insight regarding the nature of the impairment contributing to non-fluent speech. Poeck (1983) suggests that characterizing fluency by singling out one measure would not wholly represent a participant's performance of speech. The idea that multiple metrics may better indicate speech fluency is also supported by perceptual studies that suggest that listeners gauge the flow of speech using multiple cues (Park et al., 2011). Various objective measures of speech production therefore also are used for evaluating speech fluency, including global speech timing measures (e.g., speech rate) and measures without the timing component (e.g., phrase length, word count; e.g., Benson, 1967; Feyereisen, Verbeke-Dewitte, & Seron, 1986; Goodglass & Kaplan, 1972; Goodglass, Quadfasel, & Timberlake, 1964; Gordon, 1998; Yorkston & Beukelman, 1980).

Previous aphasia research investigating cognitive-linguistic abilities and speech fluency has shown that impaired lexical, syntactic, phonological, and semantic processes play a role in less fluent speech (e.g., Drummond, Gallagher, & Mills, 1981; Lambon Ralph, Snell, Fillingham, Conroy, & Sage, 2010; Wayland & Taplin, 1982). In addition, non-fluent speech associated with Broca's aphasia has been hypothesized to reflect participants' inability to generate an efference copy (Fridriksson et al., 2015; Fridriksson et al., 2012). Namely, patients with damage to the left inferior frontal gyrus, especially pars opercularis, speak more fluently when mimicking an audio-visual speech model in real time (speech entrainment) as indexed by an increase in the number of different words produced per minute during speech entrainment compared to spontaneous speech (Fridriksson et al., 2015; Fridriksson et al., 2012). These results suggest that these participants are not incapable of the articulations themselves, but that they may lack an online model or efference copy, to which they can match speech production. The external audio-visual speech model provides that missing online model, enabling more fluent speech production (Fridriksson et al., 2012; Hickok et al., 2011). However, the relationship between non-fluent speech and the integrity of the efference copy, as reflected by non-fluent speakers' responses to speech entrainment, has yet to be firmly established.

The purpose of this study therefore was to investigate the relationship between speech fluency and participants' performance on multiple speech and cognitive—linguistic mechanistic predictor measures, including response to speech entrainment (i.e., speech entrainment response), which could elucidate the cognitive mechanism responsible for non-fluent speech. Rather than using subjective fluency ratings obtained from the WAB, principal component analysis (PCA) with varimax rotation was conducted on five objective

measures of speech production to determine a primary "speech fluency" factor that accounted for the maximum amount of shared variance among all speech production measures. The current study was not a perceptual study; listeners were not asked to judge speech fluency. Thus, referenced "speech fluency" benefits during speech entrainment compared to spontaneous speech may not be associated with listeners' auditory perceptual judgments of speech fluency. While earlier aphasia studies investigating speech fluency have employed data reduction techniques (e.g., Vermeulen, Bastiaanse, & Van Wageningen, 1989; Wagenaar, Snow, & Prins, 1975), findings from these prior studies are unclear due to methodological concerns (Feyereisen, Pillon, & Partz, 1991). Similar statistical techniques also have been used in related aphasia studies examining structural brain damage in relation to speech and language impairment (e.g., Butler, Ralph, & Woollams, 2014; Fridriksson et al., 2016; Halai, Woollams, & Ralph, 2017; Lambon Ralph et al., 2010; Wang, Marchina, Norton, Wan, & Schlaug, 2013). Following the PCA, the first extracted principal component (i.e., Factor 1), which we propose is the best indicator of non-fluent speech in the study sample, was entered into a stepwise regression analysis as the predicted variable. A set of explanatory variables (i.e., mechanistic cognitive-linguistic predictor variables) was then used to determine the underlying mechanisms that give rise to non-fluent speech in chronic stroke.

Method

Participants

Data from 88 participants ($M_{age} = 58 \pm 10$ years; 34 women, 54 men) who survived a lefthemisphere stroke were selected from a larger dataset. All participants were at least six months post stroke, reported no history of neuropsychiatric disease or developmental language impairment, and varied in aphasia subtype presence and severity as indexed by the WAB (Kertesz, 1982, 2007). Participants were classified as follows: (a) anomic (22 participants), (b) Broca's (24 participants), (c) conduction (11 participants), (d) global (4 participants), (e) Wernicke's (8 participants), and (f) no aphasia (19 participants). Stroke survivors without aphasia were included in the study because current classification schemes may miss mild language impairments (Gordon, 1998). For all participants with aphasia, the mean WAB Aphasia Quotient (WAB-AQ) reflecting aphasia severity was 63.1 ± 23.6 . The mean WAB-AO for all patients without aphasia was 98.1 \pm 1.0. WAB-AO scores >93.8 indicate language performance within normal limits. The Apraxia of Speech Rating Scale (ASRS; Strand, Duffy, Clark, & Josephs, 2014) was used to determine the presence and severity of apraxia of speech and dysarthria, because both apraxia of speech and dysarthria frequently co-occur with non-fluent aphasia variants. At the time of this study, ASRS scores were available for 20 of 28 participants with non-fluent aphasia variants and were characterized as follows: (a) Broca's with apraxic speech characteristics (13 participants), (b) Broca's with apraxic and dysarthric speech characteristics (5 participants), and (c) Broca's without apraxic or dysarthric characteristics (2 participants). Although ASRS scores were not available for eight participants (e.g., ASRS was not completed), it is likely that at least mild apraxia of speech (AOS) and/or dysarthria was present for these participants, because AOS and dysarthria frequently co-occur with aphasia. AOS and/or dysarthria

severity ranged from mild to severe. Informed consent was obtained from all participants, and the Institutional Review Board at the University of South Carolina approved this study.

Speech fluency measures

Participants underwent a comprehensive assessment battery administered as part of a larger study. Speech fluency measures were obtained from picture descriptions (i.e., picnic scene) acquired during administration of the WAB (Kertesz, 1982, 2007). The picnic scene thus generated all five speech fluency measures obtained for use in the current study: (a) speech rate (syllables/second), (b) mean silent pause duration (seconds), (c) the number of silent pauses, (d) the number of syllables, and (e) the number of different words produced in a given speech sample. All measures are described in the following paragraphs. All participants described the picnic scene, which was visually displayed for two minutes on a computer screen or a printed version of the scene. Participants were encouraged to describe the scene using complete sentences until the two minutes had elapsed. Participants were audio—video recorded in a quiet room, and audio—video recorded speech samples were saved directly to a computer for offline acoustic analysis and orthographic transcription.

The entire duration of each speech sample was segmented into runs and pauses using speech analysis software, excluding intervals of examiner speech (Praat; Boersma, 2001). A speech run was defined as a stretch of speech bound by a silent pause greater than 200 ms (Tjaden & Wilding, 2004). Standard acoustic criteria were used to identify run onsets and offsets (for details see Feenaughty, Tjaden, Benedict, & Weinstock-Guttman, 2013). For each participant, the number of syllables for each speech run was tallied. Speech rate in syllables per second was calculated by dividing the total number of syllables by the total sample duration including articulation and pause time. Articulatory rate (syllables/second) was also calculated by counting the total number of syllables and dividing by the total articulation time. Syllables in neologisms and paraphasias were tallied, as well as repeated syllables. Syllable productions did not include filled pauses (i.e., uh, um). Syllable repetitions such as "ca-cat" were recorded as two syllables. Note that speech rate was used in the PCA, while articulatory rate was used in the stepwise regression analysis (see *Data Analyses* section). For mean silent pause duration, silent pause durations (i.e., greater than 200 ms) for the speech sample were averaged to yield an average silent pause duration for each participant. The number of silent pauses was also tallied to obtain a total number of silent pauses produced in a given speech sample.

In addition to the measures obtained from acoustic analysis, the total number of different words was counted for each speech sample to assess speech fluency without the timing component. All speech samples therefore were orthographically transcribed by trained research assistants and checked by a certified SLP with expertise in aphasia and transcription. Discrepancies were resolved through discussion and forced-choice agreement. All attempted word productions were tallied regardless of detected errors (e.g., paraphasias and neologisms). However, word counts excluded filled pauses as well as disfluency-related errors such as part word repetitions and sound prolongations. For example, syllable repetitions such as "ca-ca-cat" and prolongations such as "s-s-sand" were recorded as one word.

Reliability

Intra-judge and inter-judge reliability of acoustic measures were calculated for approximately 10% of the speech samples. Ten samples were randomly selected, and measures were repeated. Average absolute measurement and standard deviation were used to index reliability. Pearson product correlation coefficients were also obtained (see Feenaughty et al., 2013). For intra-judge reliability, the absolute average measurement error and standard deviations were .10 syll $\rm s^{-1}$ (.12 syll $\rm s^{-1}$, where syll = syllable), .05 syll $\rm s^{-1}$ (. 05 syll $\rm s^{-1}$), and .08 s (.15 s) for articulatory rate, speech rate, and mean silent pause duration, respectively. Intra-judge Pearson correlations were all greater than .98. For interjudge reliability, the absolute average measurement error and standard deviation were .12 syll $\rm s^{-1}$ (.07 syll $\rm s^{-1}$) for articulatory rate, .03 syll $\rm s^{-1}$ (.03 syll $\rm s^{-1}$) for speech rate, and .04 s (.07 s) for mean silent pause duration. Inter-judge Pearson correlations were all greater than . 96.

Intra-judge and inter-judge reliability for the total number of words, prior to consensus decisions, and the total number of different words was calculated for approximately 10% of the speech samples. Nine samples were randomly selected, and word counts were repeated. Pearson product correlation coefficients were used to index reliability. For intra- and interjudge reliability, correlation results for both word count measures were greater than 98%.

Mechanistic predictor variables

All participants underwent clinical speech and language assessment conducted by certified SLPs. Testing included the *Philadelphia Naming Test* (PNT; Roach, Schwartz, Martin, Grewal, & Brecher, 1996), the Pyramids and Palm Tree Test (PPTT; Howard & Patterson, 1992), and the Argument Structure Production Test (ASPT_A) of the Northwestern Assessment of Verbs and Sentences (NAVS; Thompson, 2011). Each assessment was administered and scored according to standard test procedures. In addition, participants' ability to mimic speech in real time (speech entrainment response) was compared to their spontaneous speech. Methodological details concerning a similar measure and the behavioural tasks were previously reported (Fridriksson et al., 2015; Fridriksson et al., 2012). Briefly, the participant is asked to mimic in real time the speech that is heard through headphones and matched by the video of the speaker's mouth shown on a laptop screen. Predefined scripts are used in the entrainment session, which correspond to daily-life activities such as how to make scrambled eggs. Details to evaluate speech entrainment response are described below. Finally, articulatory rate was also obtained as described in the Speech Fluency Measures section, above. Each behavioural test is briefly described in the following sections.

Philadelphia Naming Test (PNT; Roach et al., 1996)

The PNT was used as a measure of lexical retrieval impairment. The PNT consists of 175 pictured nouns that vary in frequency of occurrence and syllable length. Participants were instructed to name each picture displayed on a computer screen. Each picture was displayed for a maximum duration of 10 s. The total number of correct items named was used in the statistical analysis. Start–stop–restart naming attempts that were ultimately correct were not

classified as errors. Neologisms and semantic or phonological paraphasias, however, were considered errors.

Pyramids and Palm Tree Test (PPTT; Howard & Patterson, 1992)

The PPTT was used to assess non-verbal semantic processing. The PPTT involves pictures that are presented three at a time. After three practice trials, the participant is instructed to select one of two pictures that is semantically related to a target picture. The number of correct responses was used in the regression analysis.

Northwestern Assessment of Verbs and Sentences (NAVS; Thompson, 2011)

To evaluate grammatical processing, the Argument Structure Production Test (ASPT_A) of the NAVS was employed. This subtest presents participants with 32 action scenes, in which participants are provided with nouns and verbs that correspond to each scene. Participants were instructed to produce a sentence aloud using all words and pictures for each scene. Participant responses were orthographically transcribed to obtain the total number of sentences produced with no argument structure errors (i.e., verb and all argument structures present and produced in the correct order) for use in the regression analysis.

Speech entrainment response and articulation rate

To evaluate the participants' response to speech entrainment, speech entrainment response was calculated as a change or difference in the average number of different words produced during the speech entrainment task, relative to the average number of different words produced during spontaneous speech. To obtain the average number of different words produced in spontaneous speech, all participants described three pictures including the picnic, the cookie theft, and the circus scenes from the WAB (Kertesz, 1982, 2007), the Boston Diagnostic Aphasia Examination (Goodglass, Kaplan, & Barresi, 2001), and Apraxia Battery for Adults-Second Edition (Dabul, 2000), respectively. Each picture was displayed for 2 minutes. Participants were instructed to describe what was happening in each picture and to try to talk in complete sentences. During the speech entrainment task, participants mimicked three short, videotaped scripts that included a speaker whose face was shown below the nose and presented on a computer screen and heard via headphones. These speech entrainment scripts varied in topic, length (i.e., between 48 and 58 words), and duration (i.e., approximately 40-45 s). The videos were presented using Psychtoolbox (Brainard, 1997; Kleiner, Brainard, & Pell, 2007; Pelli, 1997) and Matlab software (Mathworks, Inc., Natick, MA). Participants were instructed to mimic each model in real time. Participants' recorded speech samples were saved directly to a computer for subsequent orthographic transcription by trained research assistants and were checked by a certified SLP. Discrepancies were resolved through discussion. Because recording times differed for each speech task, speech samples were adjusted by dividing the number of words by the sample duration. Intervals of extraneous speech that were unrelated to the task, as well as periods of laughing and coughing, were excluded.

Finally, articulation rate measured as syllables per second was used to assess speech motor processes. As described previously, articulation rate was calculated by counting the total

number of syllables produced in a speech sample (i.e., picnic scene) and dividing by the total articulation time, excluding pauses.

Data analyses

PCA with varimax rotation was performed on all speech fluency measures to determine an optimal, smaller set of speech production variables, which could explain the variance in the speech production data. Principal components were extracted with eigenvalues greater than one, representing a meaningful amount of the total variance of speech performance captured by a given component (Kaiser, 1960). The first extracted principal component (i.e., Factor 1), which we propose as the best indicator of speech fluency in the study sample, was entered into a subsequent multiple linear stepwise regression analysis as the predicted variable. Descriptive statistics (means and standard deviations) were used to further characterize all variables, and correlation analysis was also used to investigate the strength of association between the various speech and language measures used in the study. To compare across variables with different scales, all variables were standardized (z-score) prior to the statistical analysis by subtracting the observed value from the mean and dividing by the standard deviation. Scores obtained from the NAVS (ASPT A) were standardized according to testing protocols. Further, outcome values were reversed as needed before calculating standard scores, such that higher scores indicated more fluent speech across each measure. Finally, to illustrate the relationship between speech fluency (Factor 1) and significant mechanistic predictor variables (i.e., PNT scores, ASPT A scores, speech entrainment response scores, and articulation rate), a composite fluency score was calculated by adding the z-scores for the speech production variables that loaded most heavily onto Factor 1 (see Figure 1). Because of possible overlap between the predicted variable (i.e., Factor 1) and predictor measure (i.e., change in number of different words) the analyses were repeated excluding the number of different words in the PCA and subsequent stepwise regression analysis. Significant differences were not obtained as a result of these analyses, and therefore the number of different words was retained in the final PCA analysis. Statistical analyses were performed using SPSS (Version 24) and a .05 alpha level.

Results

Principal component analysis

Participants' performance on the speech and language measures varied considerably as evidenced by the high standard deviations (Table 1). Table 2 includes bivariate Pearson correlation coefficients showing that most of the speech production measures were related. In an effort to obtain a speech production variable that best explains fluency variation, all speech fluency variables were entered into a PCA. PCA with varimax rotation produced a two-factor solution, which when combined accounted for 88.8% of the total variance in participants' speech production ability. Figure 2 shows the factors and their corresponding component loadings for each speech fluency variable. Factor 1 accounted for 66.5% of variance in speech performance with the variables of speech rate (.969), the number of syllables (.938), and the number of different words (.939) loading most heavily. Factor 2 accounted for 22.4% of variance in speech performance. The speech fluency variables that loaded most heavily on Factor 2 were the number of silent pauses (.961) and mean silent

pause duration (.652). These results suggest a notable dissociation between speech output units and their overall speech timing (i.e., number of words, number of syllables, speech rate) and pausing characteristics (i.e., silent pause frequency and duration). Because more than half of the variance in speech performance was accounted for by the first extracted component, Factor 1 was henceforth labelled "speech fluency" and was entered as the predicted variable in the regression analysis, below.

Stepwise regression results

Table 2 also reports the correlations among the mechanistic predictor variables of speech fluency. Although many of these variables were significantly correlated, multicollinearity was not observed, as indicated by variance inflation factor values that were no greater than 2.007, suggesting minimal measurement redundancy among the independent variables (Cohen, Cohen, West, & Aiken, 2003). Thus, all variables were retained and were entered as predictors of speech fluency (i.e., Factor 1). As indicated in Table 3, four significant models emerged. Model 1, which accounted for almost 70% of the variance in speech fluency, included speech entrainment response as the best predictor of speech fluency, R(1, 33)72.71, p < .001, $R^2 = .68$. Model 2 included speech entrainment response and articulation rate, F(1, 32) = 7.98, p < .01, $R^2 = .75$. Model 3 included speech entrainment response, articulation rate, and ASPT_A, F(1, 31) = 4.66, p < .05, $R^2 = .78$. Finally, Model 4 included speech entrainment response, articulation rate, ASPT A, and PNT scores, H(1, 30) = 5.50, p< .05, $R^2 = .81$. Beyond speech entrainment response, articulatory rate accounted for an additional 6% of variation in speech fluency. Beyond speech entrainment response and articulation rate, syntactic processing (ASPT A) accounted for 3% of the variation. Lexical retrieval (PNT) also accounted for an additional 3% of the variance in speech fluency beyond speech entrainment response, articulation rate, and syntactic processing. The measure of semantic processing (PPTT) was not a significant predictor of speech fluency for any model. Figure 1 illustrates the relationship between speech fluency and the significant mechanistic predictors of speech fluency that emerged in the regression analysis.

Discussion

The primary purpose of this study was to investigate the underlying mechanistic factors that cause non-fluent speech in aphasia. Multiple stepwise linear regression analysis revealed four significant speech fluency prediction models. The fourth significant model was comprised of all predictor variables, except for semantic processing. Participants' speech entrainment response was the greatest independent predictor of speech fluency. When compared to spontaneous speech, we suggest that speech entrainment response gauges efference copy intactness. In the paragraphs below, findings from the PCA and the regression analyses are considered, followed by theoretical and clinical implications.

PCA indicated that a combination of reduced overall speech timing (i.e., speech rate) and quantity of speech (i.e., the number of syllables and different words) best represented non-fluent speech during spontaneous picture descriptions. Similar studies investigating speech fluency patterns and language characteristics revealed that reduced mean length of utterances, number of conjunctions and auxiliary verbs, and the number of words produced

per minute as well as speaking rate also contribute to reduced speech fluency (e.g., Vermeulen et al., 1989; Wagenaar et al., 1975). Although these prior studies utilized similar data reduction techniques, the design of these studies and the current study differed. In the current study, PCA with varimax rotation minimized redundancy among fluency measures to determine a single factor reflecting non-fluent speech in the study cohort for the regression analysis. In contrast, previous studies determined the underlying language impairment based on subgroups of speech and language characteristics extracted from PCA (e.g., Vermeulen et al., 1989; Wagenaar et al., 1975). The current study also focused on quantitative measures of speech fluency, rather than on subjective measures of speech flow and language characteristics. Nonetheless, the current results are in line with previous studies suggesting that overall reduced speech timing and quantity of speech may best describe speech fluency in patients with non-fluent aphasia variants.

The current participant sample was heterogeneous concerning aphasia presence, type, and severity. Participants also varied concerning the presence of apraxia of speech and dysarthria characteristics. To better understand the nature of these speech characteristics and how they differed between non-fluent and fluent aphasia variants, a qualitative post hoc analysis was conducted. Participants classified with non-fluent speech variants produced slower speech rates, fewer different words, and fewer syllables. Although it is not clear what behavioural factors contributed to speech fluency, problems with planning motor control and neuromuscular involvement probably contributed to these speech characteristics, in addition to cognitive—linguistic deficits. The finding that participants classified with non-fluent speech variants produced slower speech rates, fewer different words, and fewer syllables also supports extant studies suggesting that a single measure of speech production may not wholly indicate the nature of fluency impairments in aphasia (Feyereisen et al., 1991; Poeck, 1983).

When predicting speech fluency from mechanistic measures of lexical, grammatical, and articulatory processing as well as speech entrainment response, a significant regression model that accounted for 81% of the variance was obtained. Although measures of lexical, grammatical, and articulatory processing abilities separately accounted for a small, yet significant proportion of the variance in speech fluency, the greatest amount of variance was clearly attributed to participants' speech entrainment response, which independently explained 68% of the variance in speech fluency. When the regression analysis was repeated excluding speech entrainment response, articulatory (54%) and grammatical (7%) processing abilities were independent significant predictors of speech fluency and together accounted for a somewhat modest portion of the variance, 61%. To explore the impact of the overall length of a given speech sample, we replaced the number of different words in the PCA with type token ratio and repeated the regression analysis again. Although variables were to some extent reordered, similar results were obtained. That is, regression results indicated that 63% of the variance in speech fluency was accounted for by participants' speech entrainment responses when type token ratio was used versus 68% of the variance indicated in the initial PCA analysis that used the number of different words.

Speech production and monitoring requires internally generated efference copies of speech motor commands projected to the auditory system in order to detect errors between intended

motor commands and actual speech feedback (Hickok, 2012; Houde & Nagarajan, 2011). Patients with damage to the left inferior frontal gyrus, especially pars opercularis, speak more fluently during speech entrainment as indexed by an increase in the number of different words produced per minute during speech entrainment compared to that during spontaneous speech (Fridriksson et al., 2015; Fridriksson et al., 2012). Given that participants' speech entrainment response explained 68% of the variance in speech fluency, impaired speech fluency post stroke is probably a consequence of a degraded internal speech production monitoring mechanism in many speakers with aphasia. Thus, results suggest that what these patients may lack is an online model, an efference copy, to which they can match their speech production (Fridriksson et al., 2012; Hickok et al., 2011).

According to both the DIVA and SFC models of speech production, two separate but interacting feedforward and feedback mechanisms make up the system required to provide online auditory and proprioceptive feedback necessary to maintain fluent speech (e.g., Guenther et al., 1998; Hickok et al., 2011). The current study was not designed to differentiate between the two models, but rather to test the efference copy mechanism that is now part of contemporary models of normal speech production. That is, both of these speech production models imply that absent or degraded efference copies would compromise the efficiency of the sensory feedback used to correct motor commands, because errors in initiation or actual production cannot be detected without accurate access to speech sound targets. The finding that the integrity of efference copy, as inferred from participants' response to speech entrainment relative to baseline (spontaneous speech), was a significant predictor of fluency in post-stroke aphasia supports this idea. Because most participants with non-fluent aphasia variants had co-occurring apraxia of speech and/or dysarthria, results also probably reflect degraded neural projections supporting feed-forward motor plans and outgoing motor commands, respectively.

Speech fluency is an important construct in the treatment of aphasia, as several speech production problems may contribute to decreased fluency following stroke (Gordon, 1998). For example, lexical retrieval or syntactic deficits may impact speech rate. However, which linguistic domains most strongly impact speech fluency in aphasia is not well understood. Although it is inherently challenging to determine the predominant underlying cause contributing to non-fluent speech on which to focus therapeutic efforts (Gordon, 1998), the current findings may have important clinical implications. For example, results suggest that the generation of efference copies or forward predictions, which may be critical for fluent speech production, may form a crucial mechanism to target in therapy. To the extent that greater change in the number of different words produced during speech entrainment compared to picture description predicted non-fluent speech (negative relationship, see Figure 1A), our findings further support therapeutic strategies utilizing external gaiting mechanisms to help initiate and monitor the flow of speech (e.g., speech entrainment, melodic intonation therapy, mirror therapy). In turn, this type of therapy may make it possible for patients with chronic non-fluent speech (with or without comorbid speech deficits) to practise speaking more fluently and thereby strengthen the generation and use of efference copies in speech motor control.

Limitations, future directions, and conclusion

Silent pause frequency and duration measures primarily loaded on to a second extracted principal component, which when combined explained the remaining 22.4% of the variance among speech fluency measures. It is important to note that speech rate was calculated using the total sample duration including pause time, and as a result Factor 1 of the PCA, to some extent, accounted for pause time. However, pause characteristics obtained during connected speech post stroke may implicate independent neurological processing deficits. Thus, future studies should investigate the underlying cognitive and linguistic mechanisms predicting pausing patterns in aphasia. Another factor to consider when interpreting results of the present study is that the general pattern of predictive factors for non-fluent speech was based on group data. Thus, although our results identified a pattern of predictive factors that are likely to explain non-fluent speech in many stroke survivors, individual stroke survivors may still present with non-fluent speech that may not be solely attributed to impaired efference copy. For example, some participants with very severe apraxia of speech do not respond positively during speech entrainment (Fridriksson et al., 2012). This finding suggests that therapeutic or compensatory strategies targeting degraded efference copy may be contraindicated. In these cases, strategies targeting motor planning may be pursued, since motor planning itself is not dependent on an efference copy.

In conclusion, the results of this study suggest that impaired efference copy may play a significant role in speech fluency independent of lexical, grammatical, and articulatory processing deficits following stroke, at least when operationally defined as the change in the number of different words produced during speech entrainment compared to picture descriptions. This does not diminish the significant contributions of lexical, grammatical, and articulatory processing deficits to speech fluency. Rather, the results highlight the complex relationship between the underlying linguistic processes required for fluent speech production and the nature of speech production characteristics. Although it remains a clinical challenge to determine the most salient factors contributing to non-fluent aphasia on which to focus therapeutic efforts, the results of this study also appear to suggest that speech entrainment ability in comparison to spontaneous speech may be an estimation of efference copy intactness. Thus, speech entrainment ability may help to focus therapeutic strategies for patients with chronic non-fluent aphasia. However, additional studies are needed to more firmly establish the relationship between non-fluent speech and metrics reflecting patients' ability to initiate or to monitor speech post stroke.

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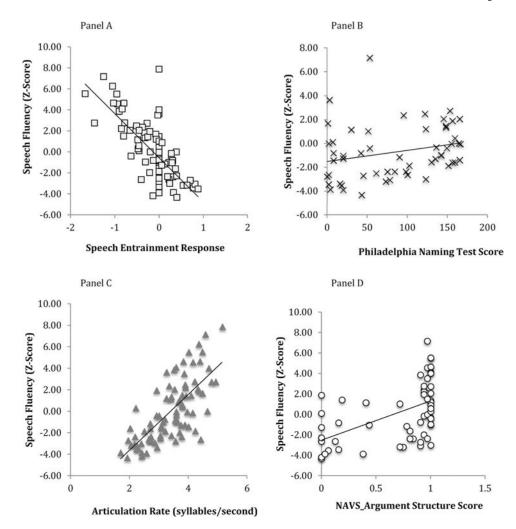


Figure 1. The relationship between speech fluency factor-based scores for participants with data in a given neurological testing domain. NAVS = Northwestern Assessment of Verbs and Sentences.

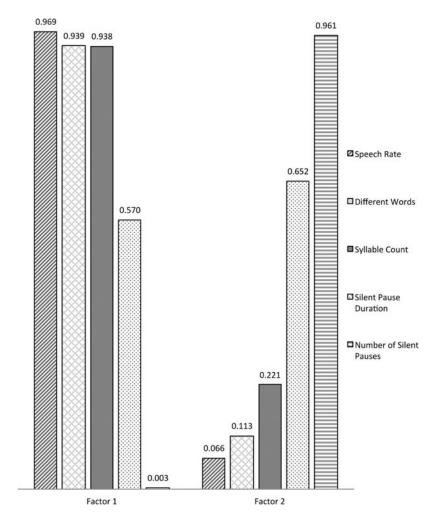


Figure 2.Loadings of each speech fluency measure on factors extracted from the rotated principal component analysis (PCA).

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 Table 1

 Descriptive statistics for speech fluency and mechanistic predictor variables.

Measures	М	SD
Speech fluency variables		
Speech rate (syll s ⁻¹)	1.52	0.85
Number of syllables	158.73	101.32
Number of different words	63.75	39.54
Number of silent pauses	42.63	15.06
Mean silent pause duration (s)	1.44	0.88
Mechanistic variables		
Philadelphia Naming Test (Lexical)	85.38	59.58
Pyramids and Palm Tree Test (Semantic)	47.35	3.71
Northwestern Assessment of Verbs and Sentences-Argument Structure (Grammatical)	0.72	0.38
Speech entrainment compared to spontaneous speech (Efference copy)	-0.24	0.59
Articulation rate (Articulatory)	3.40	0.79

Note: syll = syllable.

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Table 2

Pearson product-moment correlations among speech fluency variables and mechanistic predictor variables.

	Variables	-	73	8	4	w	2 3 4 5 6	7	∞	6	10
Spee	Speech fluency										
ij	1. Speech rate (syll s ⁻¹)	-									
5	Number of syllables	.903	_								
3.	Number of different words	. 865	.930	1							
4.	Number of silent pauses	946	.270	.164	_						
5.	5. Mean silent pause duration (s)	889.	575.	.524	.491	_					
Mecl	Mechanistic										
9.	Philadelphia Naming Test (Lexical)						_				
7.	Pyramids and Palm Tree Test (Semantic)						.428	_			
<u>«</u>	Northwestern Assessment of Verbs and Sentences-Argument Structure (Grammatical)						.651	.623	_		
9.	Speech entrainment compared to spontaneous speech (Efference copy)					ı	.356	356177364	364	-	
10.	10. Articulation rate (Articulatory)						.187	.293	.300668	668	-

Note: syll = syllable. Alpha level = .05. Bold font indicates significant correlations at p < .05.

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Table 3

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Model	R	R^2	R ² change	F change	d
1	.829	889.	889.	72.715	000.
2	998.	.750	.062	7.985	.008
3	.885	.783	.033	4.662	.039
4	.904	.816	.034	5.500	.026

Note: Model 1 = speech entrainment response; Model 2 = speech entrainment response and articulation rate; Model 3 = speech entrainment response, articulation rate, and Philadelphia Naming Test.