Introduction

Research has shown that therapy can significantly improve the communicative success of patients with aphasia. In spite of progress made in the field of aphasia rehabilitation, questions remain regarding the influence of factors such as severity of aphasia and measures of cognitive and linguistic ability on language recovery. A major limitation currently facing clinicians is the inability to predict therapy outcomes or tailor treatment to individuals.

We aim to introduce a fundamentally new approach that looks beyond language, proposing that the answer to developing efficacious, individually tailored therapies lies in a better understanding of the supporting systems and networks of general learning. Learning is integral to the processes of forming associations, recalling information and applying rules (Seger & Miller, 2010 for review). Learning requires attention, strategy use, feedback monitoring and integration, skills likely to contribute to the process of achieving gains through therapy. Thus, we suggest that predicting whether a patient will improve following therapy instruction may depend more upon that individual's ability to *learn new information* in general than upon a specific ability to *relearn or re-access language*.

In support of this hypothesis are recent neuroimaging studies that have found success with language therapy to be associated with structures and functional networks associated with learning and memory; rather than with structures considered essential to language (Goldenberg & Spatt, 1994; Meinzer et al., 2010; Menke et al., 2009). In addition, a recent study by Vallila-Rohter & Kiran (2013) suggests that patients with aphasia vary in their ability to learn non-linguistic categories.

We propose that learning ability is yet another factor that contributes to treatment outcomes. In the current study we explore the relationship between learning ability and progress with language therapy. We hypothesize that non-verbal learning phenotype (learning slope) will be positively associated with treatment outcomes.

Methods

Participants

To date, 28 patients with aphasia (16 males) have participated, with 10 additional patients anticipated to complete the study. Ages range from 34 to 87 (mean = 60.4). All participants had a single left hemisphere stroke, were premorbidly right handed and were at least six months post stroke at the time of the study. All participants were tested on the Western Aphasia Battery (WAB, Kertesz, 1982), Boston Naming Test (BNT; Kaplan, Goodglass, & Weintraub, 1983) and Cognitive Linguistic Quick Test (CLQT; Helm-Estabrooks, 2001) to obtained standardized cognitive-linguistic measures. All participants presented with sentence comprehension deficits and were enrolled in a sentence comprehension treatment described below. Participants also completed non-linguistic category learning tasks.

Procedures

Treatment. Prior to initiating therapy, patients completed three baselines as part of a single subject, multiple baseline design (Thompson, 2006). During therapy, patients were either presented with pictures depicting the action of a sentence or with paper dolls representing nouns in the sentence (see Kiran et al., 2012). Pictures or paper dolls were used in therapy to demonstrate the thematic roles of each constituent of target sentences. During weekly monitoring batteries, patients were either instructed to select the illustration of the target sentence from a field of two; or were asked to use paper dolls to enact thematic roles.

Therapy continued for ten weeks or until patients reached 80% accuracy on monitoring batteries for two consecutive weeks. After treatment was terminated, patients completed three post-treatment monitoring batteries.

Learning task. Stimuli for the learning task are fictional animals, first implemented by Zeithamova et al. (2008) and utilized in Vallila-Rohter and Kiran's (2013) study. Animals vary on ten binary dimensions (color, body shape, pattern, etc) and are organized into two categories based on the number of features shared with each of two prototypical animals. In this manner, categories are continuous, with an internal structure. Categorization rates are expected to match the percentage of feature overlap with each prototype (i.e. animals with an 80% feature overlap with prototype A are expected to be labeled as category A in 80% of trials and category B in 20% of trials).

Learning tasks were computer based and comprised of ten-minute training and ten-minute testing phases. In training, animals were presented one at a time on a computer screen and participants were instructed to guess to which of two categories each animal belonged. After a button response was made, participants received feedback in the form of a check mark or an "x" indicating whether their response was correct or incorrect. Participants were instructed to attend to all features.

In testing phases that followed training, participants categorized novel animals and prototypes, this time receiving no feedback related to accuracy. Data collected on accuracy rates quantified patient abilities to quickly integrate feedback and successfully learn novel categories.

Data Analysis

Treatment data. For treatment data, effect sizes were calculated for each patient based on average pre-treatment and post-treatment probe scores divided by the standard deviation of the baseline. This measure was selected as a better match for learning slope than an overall percent change.

Category learning data. Research has suggested that participants can use multiple strategies in probabilistic category learning (Gluck et al., 2002). For the current study, we were interested in examining learning results obtained through multi-cue strategies, as these approaches place the highest demands on hypothesis formation, testing, feedback monitoring and integration. Raw data were examined to identify patients who attended to only one feature (produced an 85% to 100% cue-outcome response rate on a single feature).

Next, accuracy scores were converted into %B responses and analyzed as a function of feature overlap with prototype B. Individual results were reduced to a single slope score (learning phenotype), a slope of positive ten representing ideal learning.

Results

Preliminary analyses of category learning data revealed that despite instructions to attend to all features, 8 out of 28 patients used a one-cue strategy. We suspect that the demands of multi-dimensional learning may be too complex for these patients. Slope data from these 8 participants were not included in further analyses. Raw scores for the remaining 20 patients suggested the use of a multi-cue strategy, in which category responses were based on multiple animal features.

Analyses of effect size and learning phenotype (slope) produced a significant correlation, $r(18) = .52$, $p = .02$. Interestingly, none of the other correlations with effect size were significant, AQ, $r(17) = .03$, $p = .88$; BNT score, $r(18) = -0.06$, $p = .78$; attention, $r(18) = .23$, $p = .32$; memory, $r(18) = .33$, $p = .16$; executive function, $r(18) = .31$, $p = .18$; and visuospatial scores, $r(18) = .37$, $p = .11$. In addition, learning phenotype was not correlated with severity of aphasia AQ $r(17) = .05$, $p = .84$ or any additional cognitive-linguistic measure.

Discussion

These results support the hypothesis that non-verbal learning phenotype is positively associated with treatment outcomes. We propose that many skills necessary for successful non-linguistic category learning (stimulus processing, hypothesis formation, feedback monitoring and integration) likely play an important role in the relearning or re-accessing of language brought about through therapy. Effect size was not associated with additional cognitive-linguistic measures, nor was learning phenotype predicted by these measures. Findings support the proposal that learning ability is an additional, unexplored factor contributing to aphasia rehabilitation with the potential for improving the predictability of outcomes.

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