Learning ability in post-stroke aphasia: Success, strategy use and implications for therapy

by

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Abstract

Aphasia is an impairment in the expression or comprehension of language that results from stroke, traumatic brain injury or progressive neurological disease. Approximately one million people in the United States suffer from aphasia, with the prevalence projected to increase to two million by 2020. Research has shown that speech-language therapy, the treatment for aphasia, can significantly improve people's ability to communicate. However, a major limitation in the field of aphasia rehabilitation is the lack of predictability in patients' response to therapy and the inability to tailor treatment to individuals.

We hypothesize that learning represents a critical, underexplored factor in aphasia rehabilitation. Predicting whether a patient will improve following therapy may depend more upon that individual's ability to learn new information in general than upon a specific ability to relearn and master language.

In this thesis I report a series of experiments that introduce a new approach that looks beyond language, proposing that the answer to developing efficacious, individually tailored therapies lies in a better understanding of the mechanisms of nonverbal learning in individuals with aphasia. We first explore learning success on a test of nonlinguistic category learning to examine whether learning differences arise among individuals with aphasia and non-aphasic controls. In Experiment 2, we probe the impact of stimulus manipulations on learning success. Experiment 3 presents an investigation into the relationship between learning score and language therapy outcomes. Finally, in Experiment 4, we examine the strategies used to perform our task in order to better understand how information is processed during probabilistic category learning.

Results support the hypothesis that aphasia differentially affects language and learning networks. Instruction method and stimulus complexity were found to impact learning success and strategy use in individuals with aphasia. Furthermore, a positive correlation was found between learning scores and success with language therapy, suggesting that there is an informative relationship between learning ability and therapy outcomes.

Findings draw attention to underlying processes that have not yet been the focus of research in aphasia, yet likely contribute to outcomes with therapy and present a gateway towards individualizing therapy and improving the predictability of patient outcomes.

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1. Introduction

Imagine being a politician who loses his ability to speak to a crowd. Imagine having a PhD-level education, yet when presented with a picture of a piano, being able only to say "white.... black." Even worse, imagine seeing a picture, writing its name down, yet not being able to read your own writing to say that word. These are the types of situations that we witness every day working with patients with aphasia, patients in their 30s with young children to patients who are 80 years old.

An approximate 795,000 individuals suffer from strokes each year, with 25% to 40% resulting in aphasia (Nicholas, 2009; Roger et al., 2012), an impairment in the expression or comprehension of language. Language therapy is the predominant treatment for aphasia, and an increasing body of research is demonstrating the beneficial impact of aphasia therapy even in the chronic stages of aphasia (Bhogal, Teasell, & Speechley, 2003; Holland, Fromm, DeRuyter, & Stein, 1996; Robey, 1998; Shewan & Kertesz, 1984). While we have some understanding of how individuals with post-stroke aphasia relearn language, why some patients respond to treatment while others do not remains a looming question in the field of aphasia rehabilitation (Best & Nickels, 2000; Kelly & Armstrong, 2009).

Much progress has been made in the field, such that clinicians and researchers are equipped with means of assessing aphasia (Spreen & Risser, 2003), model frameworks of language processing and impairment that help describe the nature of deficits and guide therapy (Whitworth, Webster, & Howard, 2005), as well as multiple therapies and tasks that studies have demonstrated are efficacious in improving language function in patients with aphasia (Holland et al., 1996; Kiran & Sandberg, 2011). In spite of this progress, we still do not fully understand the mechanisms of therapy (Ferguson, 1999) nor are we able to prescribe the most appropriate treatments for patients based on their language deficits and cognitive profiles (Best & Nickels, 2000; Kelly & Armstrong, 2009).

We propose that predicting whether a patient will improve following therapy instruction may depend in part upon that individual's ability to learn new information. Brain damage that leads to language loss likely damages the overall cognitive architecture of learning and memory, an architecture that contributes nodes critical to the language reorganization network. Learning is a process that is integral to relearning language and therefore to rehabilitation, yet has received little attention in the field of aphasia rehabilitation. Our knowledge about learning ability in aphasia is limited to a few verbal learning studies described in further detail below. The fact that language is the primary deficit in aphasia, however, confounds studies of novel word learning.

This thesis investigates the nature of learning in aphasia by exploring the performance of individuals with aphasia as they complete nonlinguistic category learning tasks. We hope that through a better understanding of learning in aphasia, we can improve the predictability of therapy outcomes and begin to individually tailor treatments to individuals.

1.1. Current treatment of aphasia: Diagnosis

Prior to administering aphasia therapy, patients' needs, strengths and weaknesses are determined through a diagnostic assessment of areas such as word finding, speech fluency and phrase length, auditory comprehension skills and repetition skills, as well as an evaluation of reading and writing skills, the ability to produce volitional gestural and oral movements and the extent to which behaviors and/or responses are repetitive (Helm-Estabrooks & Martin, 2004). In addition to quantitative and qualitative characterizations of language symptoms and deficits, clinicians collect information and observations about patients' neurological, medical, occupational and educational histories as well as in the domains of cognition and emotional behaviors. Information is gathered about patients' lifestyle and activities in order to better understand their functional communication needs, motivation and environmental factors that might affect recovery.

Once strengths and weaknesses have been evaluated, the goal of therapy is to reduce the impairment produced by communicative deficits. Intervention can focus on strategies intended to help increase the efficiency of residual language capacity or can focus on developing substitutive compensatory strategies (Kiran & Bassetto, 2008; Kiran & Sandberg, 2011). While therapies have been found to be effective, time after time patients with similar degrees of language impairment show variable responses to treatment (Conroy, Sage, & Lambon Ralph, 2009; Fillingham, Sage, & Lambon Ralph, 2006; Hickin, Best, Herbert, Howard, & Osborne, 2002; Lambon Ralph, Snell, Fillingham, Conroy, & Sage, 2010). Such variability is frustrating for clinicians and patients, and suggests that critical factors are missing from the current diagnostic characterization of individuals with aphasia.

Early research demonstrated that the severity of language impairment and lesion size present important predictors of spontaneous recovery (Goldenberg & Spatt, 1994; Pedersen, Vinter, & Olsen, 2004; Plowman, Hentz, & Ellis, 2012). In the chronic stages of aphasia recovery, however, few measures stand out as reliable predictors of outcomes with therapy. Researchers have suggested that cognitive deficits may be accountable for some of the variability observed with communicative success and treatment outcomes in aphasia (Fridriksson, Nettles, Davis, Morrow, & Montgomery, 2006; Lesniak, Bak, Czepiel, Seniow, & Czlonkowska, 2008; Peach, Rubin, & Newhoff, 1994). An increasing body of work has explored aspects of cognition that might be important towards constructing and retrieving language, such as attention (Erickson, Goldinger, & LaPointe, 1996; Hula & McNeil, 2008), executive function (Zinn, Bosworth, Hoenig, & Swartzwelder, 2007), concept knowledge (Chertkow, Bub, Deaudon, & Whitehead, 1997) and memory (Helm-Estabrooks, 2002; LaPointe & Erickson, 1991). Cognitive-linguistic factors such as these are often characterized prior to therapy via standardized assessments (Helm-Estabrooks, 2001).

Language factors of oral expression (i.e. naming ability, syntax) and comprehension (i.e. oral and written) have also been identified as potential prognostic factors and are often extensively assessed at the onset of therapy. Diagnostics related to core components of language production and comprehension are often informative for the selection of appropriate targets for (El Hachioui et al., 2013). These measures however, frequently do not suffice to explain observed treatment outcomes. Initial aphasia severity continues to stand out as one of the measures related to language recovery (Plowman et al., 2012).

Studies probing these factors have provided insight into linguistic and cognitive-linguistic deficits that arise in aphasia; but learning remains absent from this picture, and the problem of predictability of outcomes persists. We propose that learning ability represents one of the barriers hindering our ability to predict which individuals will improve following therapy and which will not (see Figure 1.1).

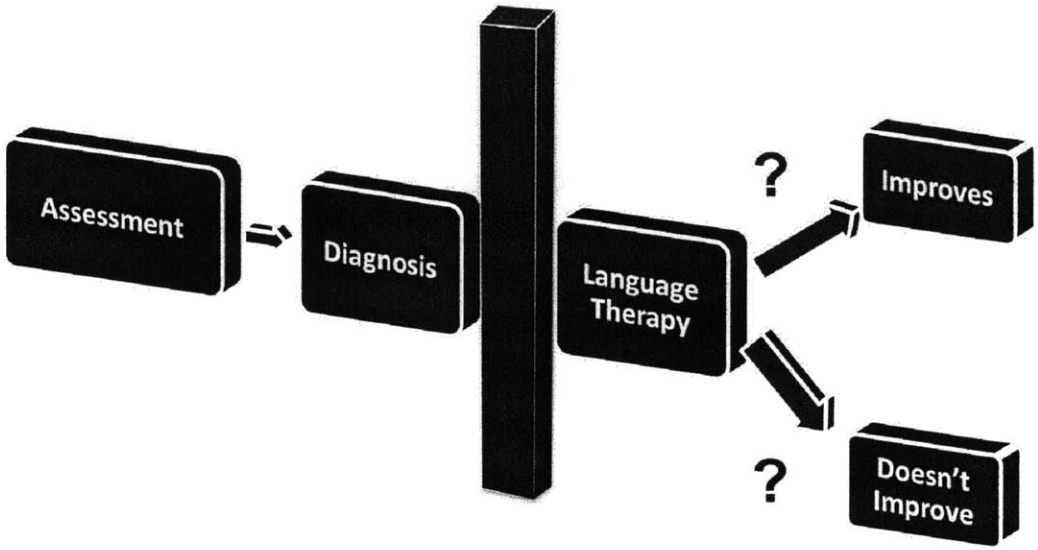

Figure 1.1: Schematic suggesting that critical factors are missing from the current diagnostic characterization of individuals with aphasia and hinder our ability to predict therapy outcomes.

1.2. Learning in aphasia: What is known

Currently, our understanding of learning in aphasia is limited to studies focused on novel word learning. In an early study of verbal learning, Grossman & Carey (1987) tested five control participants and 15 patients with aphasia; eight characterized as Broca's aphasics and seven as fluent. After exposing participants to an unfamiliar color term "bice" in naturalistic contexts, participants were asked to make grammaticality and semantic classification judgments about the word. Researchers found that different learning profiles surfaced in Broca's and fluent aphasics. Broca's patients, who traditionally present with deficits in grammar and sentence formulation, demonstrated control-like object classification of color but impaired grammaticality judgments. In contrast, fluent patients, who traditionally present with comprehension deficits, demonstrated control-like grammaticality judgments with impaired object classification. Not surprisingly, researchers concluded that processing demands were similar for newly acquired and familiar language skills.

This conclusion was later supported by Gupta et al. (2006), who found differential phonological and semantic learning abilities in patients, which were predicted by standardized composite measures of phonological and semantic processing abilities. Thus, the linguistic strengths and weaknesses of individuals with aphasia have been found to impact their ability to engage in new word learning.

Freedman and Martin (2001) expanded upon these findings, exploring the impact of phonological and semantic short-term memory (STM) skills on patients' abilities to learn Spanish translations of common words (new phonological learning) and new definitions for familiar words (semantic learning). Results demonstrated that successful learning of Spanish translations correlated with high phonological STM scores while new definition learning correlated with high semantic STM scores. These findings demonstrated how verbal cognitive strengths, in addition to linguistic strengths, might support new learning. Novel word learning has been shown to be possible under incidental learning conditions (Breitenstein, Kamping, Jansen, Schomacher, & Knecht, 2004) and through explicit instruction (Gupta, Martin, Abbs, Schwartz, & Lipinski, 2006; Marshall, Neuburger, & Phillips, 1992; Tuomiranta et al., 2011).

Considered together, these studies suggest that patients are capable of new verbal learning and that cognitive and linguistic processing abilities have an impact on learning. Despite these contributions however, our understanding of learning in aphasia is still limited, because all recent studies explore *verbal* learning.

1.3. Learning in other clinical populations

Though little is known about nonverbal learning in aphasia, studies in other clinical populations and in healthy individuals have investigated patterns of behavior that arise during various types of nonverbal learning. Research has demonstrated that manipulations of training method, stimulus characteristics, category structure, and response selection impact learning results (Ashby, Maddox, & Bohil, 2002; Ashby, Noble, Filoteo, Waldron, & Ell, 2003; Davis, Love, & Maddox, 2009; Filoteo & Maddox, 2007; Knowlton, Squire, & Gluck, 1994; Maddox, Love, Glass, & Filoteo, 2008). Often, manipulations of task and instruction method have been found critical to promoting learning in patients with brain damage.

Patients with Parkinson's Disease (PD), for example, have shown impaired procedural-based learning, information integration and rule-based learning, particularly when stimuli pose high working memory or attention demands (Filoteo & Maddox, 2007; Filoteo, Maddox, Ing, Zizak, & Song, 2005; Price, 2006). These patients show intact artificial grammar learning (Reber & Squire, 1999; Smith, Siegert, McDowall, & Abernethy, 2001; Witt, Nuhsman, & Deuschl, 2002) and intact information integration learning under conditions of limited complexity (Ashby et al., 2003; Filoteo, Maddox, Ing, et al., 2005; Filoteo, Maddox, Salmon, &

Song, 2005). Similarly, patients with amnesia are sensitive to instruction method, demonstrating impairments in learning that involves recall and recognition (Filoteo, Maddox, & Davis, 2001; Knowlton, Ramus, & Squire, 1992), yet showing successful learning of probabilistic classification tasks (Knowlton et al., 1994).

1.3.1. Multiple memory systems for learning. The mechanism underlying the facilitation or impairment of learning for these patients is thought related to the existence of multiple memory systems that rely on different neurobiological structures and support learning in different ways. Specifically, local stimulation, functional magnetic resonance imaging (fMRI), animal studies and lesion studies have demonstrated that memory can be divided into distinct systems, with long-term memory divided into declarative memory and nondeclarative memory.

Many types of learning rely on recall of individual instances, facts or events in order to form associations between previously unrelated stimuli. This type of learning, termed declarative or explicit learning, is thought to rely heavily on the hippocampus and medial temporal lobe structures (Seger & Miller, 2010; Squire 1992 for review). Declarative systems are considered important for rule-learning and for paired-associate learning, in which participants store associations between cues and responses (Breitenstein et al., 2005; Squire, 1992; Warrington & Weiskrantz, 1982; Winocur & Weiskranitz, 1976). In addition, in their COmpetition between Verbal and Implicit Systems (COVIS) model, Ashby, Alfonso-Reese, Turken and Waldron, (1998) draw attention to the likely engagement of explicit processes in the early stages of many types of category learning (Ashby, Alfonso-Reese, Turken, & Waldron, 1998; Maddox & Ashby, 2004 for review). In these stages, learners are thought to engage logic and reasoning to form hypotheses; often verbalizeable ones. Hypotheses are then tested and results monitored, processes proposed to rely heavily on attention and working memory networks.

In contrast, unconscious systems have been thought critical for gradual learning, particularly of statistical properties, complex or abstract information, and learning via trial-by-trial feedback (Ashby, Alfonso-Reese, Turken, & Waldron, 1998; Kéri, 2003; Knowlton, Mangels, & Squire, 1996; Knowlton & Squire, 1993; Maddox & Ashby, 2004; Seger & Miller, 2010). This type of learning, termed nondeclarative or implicit learning, is carried out via automatic processes that incrementally reinforce experiences (Ashby et al., 1998; Knowlton & Squire, 1993). Research suggests that unexpected rewards trigger the release of dopamine.

Release of dopamine gradually strengthens the association between cues and responses (Seger & Miller, 2010; Shohamy, Myers, Kalanithi, & Gluck, 2008; Shohamy, Myers, Onlaor, & Gluck, 2004).

Many early seminal studies focusing on these memory systems involved patients with amnesia as they completed the weather prediction task (WPT), a task whose stimuli are four unique cards composed of geometric shapes. On each trial one to three cards are presented. Participants are instructed to guess whether each card combination predicts sunshine or rainy weather. Individual cards are probabilistically associated with one outcome or another, such that successful learning of the task is achieved through gradual, trial-by-trial learning influenced by the statistical nature of weather-card associations. Early studies found that patients with amnesia were able to engage in probabilistic learning in a manner comparable to that of healthy individuals, at least in the early phases of learning (Knowlton, Mangels, et al., 1996; Knowlton et al., 1994). Results provided evidence supportive of multiple memory system hypotheses.

Further research in patients with Parkinson's and Huntington's disease with known basal ganglia dysfunction, demonstrated that for these patients, learning of the WPT was disrupted from the onset of training (Knowlton, Mangels, et al., 1996; Knowlton, Squire, et al., 1996). Behavioral studies, paired with neuroimaging work have identified cortico-striatal mechanisms as vital systems of gradual feedback-based learning.

Though certain conditions are thought to emphasize the engagement of one system over another, research has suggested that these systems can interact or compete throughout learning (Ashby et al., 1998; Ashby & Maddox, 2011; Ashby & O'Brien, 2005; Ashby & Valentin, 2005; Cincotta & Seger, 2007; Moody, Bookheimer, Vanek, & Knowlton, 2004; Poldrack et al., 2001; Seger & Miller, 2010).

1.4. Learning in aphasia: Clinical implications

The fundamental assumption of most aphasia therapy approaches is that language can be retrained through feedback and modeling and usually involves manipulation of auditory or visual stimuli (written words, gestures or pictures) of varying complexity. Treatment aimed at improving naming and word retrieval, for example, might involve presenting a patient with a picture and asking him or her to name the picture. If the patient has trouble producing the correct word, clinicians can cue the patient with a series of cues of decreasing complexity such as providing the first phoneme of the target, providing a word that rhymes with the target, presenting the target in writing, or producing the word for repetition (Raymer & Rothi, 2001). Patients might be asked to match pictures to written words or to related categories and might be asked to produce or manipulate sentences of varying complexity.

Many aphasia therapies work towards retraining language in this manner through manipulations of auditory and visual stimuli, feedback, and modeling. Currently however, we are limited in our understanding of how patients approach such tasks. Are patients attending to all stimuli presented during therapy, or are they focusing on one modality or one stimulus item at a time? Are individuals actively integrating feedback and constructing hypotheses related to instruction and cueing? Are patients able to carry over lessons from one therapy to another? Are patients able to devise strategies to carry over what is learned in therapy into real-world communicative scenarios?

All of these are questions relevant to therapy, whose answers lie in a better understanding of the ways in which patients with aphasia process information while they are engaged in therapy tasks. In addition, as highlighted in section 1.4, method of instruction can have a profound impact on the learning outcomes of individuals with Parkinson's Disease and individuals with amnesia. Does method of instruction have similar impacts on the learning success of individuals with aphasia? If so, this has critical implications for therapy, as clinicians currently focus on *what* they are targeting in therapy, with little focus on *how* those targets are instructed.

2. Research questions and rationale

Lesion and neuroimaging research now recognizes that regions critical for language have rich bilateral functional connections with frontal, temporal and parietal regions (for review see (Turken & Dronkers, 2011) Conventional aphasia research, however, has neglected to explore the implications of disrupted networks on rehabilitation and deficits; and has not yet acknowledged the impact that brain damage produced by aphasia-inducing strokes might have on non-linguistic networks. In this thesis, we aim to introduce a new approach that looks beyond language. We aim to characterize nonlinguistic learning ability in patients with aphasia, further probing how aspects of learning might impact therapy and therapy outcomes.

To this end, experiments in subsequent chapters address each of the following questions in turn: (1) How does the nonlinguistic category learning ability of individuals with aphasia compare with the learning ability of non-aphasic, age matched controls? (2) What are the impacts of stimulus complexity and method of instruction on the learning ability of individuals with aphasia? (3) Can a behavioral measure of nonlinguistic category learning predict patient outcomes in therapy? (4) What strategies do individuals with aphasia implement during complex nonlinguistic category learning?

2.1. How does the nonlinguistic category learning ability of individuals with aphasia compare with the learning ability of non-aphasic, age matched controls?

Based on experimental paradigms well established in healthy adults and in brain damaged individuals (Filoteo, Maddox, Ing, et al., 2005; Knowlton et al., 1994; Shohamy, Myers, Grossman, et al., 2004), we have designed behavioral experiments probing abstract, novel category learning in patients with aphasia and in healthy controls. We established a probabilistic classification learning task adapting stimuli from Zeithamova, Maddox and Schnyer (2008) that engages participants in the learning of two prototypical categories. We have devised two category-learning tasks, one with instruction administered in a trial-by-trial feedback manner and another with paired-associate instruction.

We expect non-aphasic controls to learn both feedback-based and paired associate tasks efficiently. For individuals with aphasia, the literature leads to two hypotheses. Work in verbal learning has suggested that patients with aphasia are capable of new learning, learning deficits arising primarily in processing domains related to linguistic capabilities (Freedman & Martin, 2001; Grossman & Carey, 1987; Gupta et al., 2006). Therefore, one might predict that faced with nonlinguistic category learning tasks, patients will learn in a manner equivalent to non-aphasic controls. In contrast, research in other clinical populations has identified differences in nonverbal learning ability across various disorders. These findings suggest that individuals with aphasia may also show patterns of learning that are disrupted relative to non brain-damaged controls. Should individuals with aphasia show impaired patterns of nonverbal learning, results will suggest that language deficits are accompanied by deficits in the general cognitive architecture supporting learning. If differences arise, we aim to devise a metric of learning that can quantify the learning ability of individuals.

2.2. What are the impacts of stimulus complexity and method of instruction on the learning ability of individuals with aphasia?

As research has shown that manipulations of training method, stimulus characteristics and category structure contribute to learning (Ashby et al., 2002; Ashby et al., 2003; Davis et al., 2009; Filoteo & Maddox, 2007; Knowlton et al., 1994; Maddox et al., 2008); in our second experiment, we explore how manipulations to such factors impact learning in individuals with aphasia. We continue to explore the impact of feedback based versus paired-associate instruction on learning. In this experiment, we further manipulate the complexity of stimulus items seen in training.

Complexity is of particular relevance to explore in individuals with aphasia, as it is one of the factors currently examined and manipulated in language therapy protocols. Theories of aphasia rehabilitation suggest that treatment focused on complex structures might facilitate generalization to related, less complex structures (Thompson, Shapiro, Kiran, & Sobecks, 2003). Hypotheses are motivated by connectionist work that has found that retraining complex, atypical category items provides information about category breadth and variability thereby promoting broad within-category learning (Plaut, 1996). Though learning under these conditions may progress more slowly than learning concentrated on simple items, the generalization benefits are more robust than those observed following training focused on simple conditions and stimuli.

In our second experiment participants are exposed to either typical or atypical category members in training. Typical category members are stimuli that have a large feature overlap with category prototypes and thus present simple training conditions in which salient category features are consistently reinforced. Atypical category members share fewer features with category prototypes and therefore more closely resemble the complex items described by Plaut (1996), providing information about category breadth and variability.

In line with connectionist models, we hypothesize that training limited to simple, typical category members will facilitate the rapid recognition of categories. Following complex, atypical training we predict that learning will generalize to typical category items. This pattern of superior generalization may come at the cost of lower overall scores of learning.

2.3. Can a behavioral measure of nonlinguistic category learning predict patient outcomes with therapy?

In order to establish the validity of our phenotype of learning and to translate behavioral findings to the clinical setting, in our third experiment, we will examine the performance of patients with aphasia enrolled in a structured 10-week therapy program targeted at a specific aspect of their communication. We have selected a theoretically based comprehension treatment aimed at improving sentence comprehension through instruction focused on thematic role assignments.

Prior to enrolling in therapy, all patients complete behavioral nonverbal learning tasks to characterize their learning ability phenotype and also complete standardized assessments evaluating the severity of their aphasia, language and cognitive deficits. As described in the introduction, measure of aphasia severity and cognitive-linguistic strengths and deficits have previously been identified as potential prognostic factors. We will therefore examine how our metric of learning compares with other frequently examined measures.

Treatment outcomes will be measured as percent change in the target language ability, and effect sizes calculated as the difference in percent accuracy between three pre-treatment and three post-treatment baseline probes. We hypothesize that non-verbal learning phenotype (learning slope) will be positively associated with treatment outcomes.

2.4. What strategies do individuals with aphasia implement during complex nonlinguistic category learning?

Finally, in the fourth experiment of this thesis, we examine how individuals with aphasia and non-aphasic controls process information during nonlinguistic category learning. While early neuropsychological and neuroimaging studies exploring feedback-based probabilistic category learning such as the weather prediction task pointed to nondeclarative memory systems as being critical to learning, more recent research has suggested that learners actually implement various strategies when approaching these tasks (Gluck, Shohamy, & Myers, 2002). Detailed analyses of behavioral data have revealed that probabilistic learning can be accomplished through a variety of strategies that include attending to one task dimension or learning the probabilistic associations of multiple cues and outcomes (Gluck et al., 2002; Meeter, Myers, Shohamy, Hopkins, & Gluck, 2006; Meeter, Radics, Myers, Gluck, & Hopkins, 2008). Studies have shown that individuals often implement simple strategies at the onset of learning, gradually invoking more complex strategies through the course of learning. Research has identified differences in strategy implementation among healthy individuals, individuals with amnesia and individuals with Parkinson's Disease.

Our first two experiments explore how experimenter-driven manipulations impact learning. In our final study, we examine how participant-selected strategies impact success with learning. This perspective is important as it presents a means of better understanding how information is processed during learning.

In this experiment, we again examine feedback-based and paired associate learning, this time adapting strategy analyses devised by Gluck et al. (2002) and Meeter et al. (2006) to better understand the means with which controls and individuals with aphasia learn our tasks. We expect differences to arise between controls and individuals with aphasia. Specifically, we expect that individuals with aphasia will show a greater reliance on simple strategies than control participants.

2.5. Summary

The experiments of this thesis have been designed to present a comprehensive approach beginning with an investigation into how individuals learn and how that learning is susceptible to stimulus manipulations and instruction methods. We then present an exploration into the translatability of findings to a therapy setting. Finally, we examine how participant-driven processing mechanisms influence patterns of learning.

The reader will note that a small group of age and education-matched controls have been included in experiments 1, 2 and 4. This group has primarily been included to validate principles and provide a baseline for interpretation of results. Due to the inherent heterogeneity of individuals with aphasia, a relatively larger group of individuals with aphasia has been included in each experiment. We obtain standardized cognitive-linguistic measures in every experiment in order to interpret results within the context of well established and frequently referenced assessments of aphasia.

3. Experiment 1. Nonlinguistic learning and aphasia: Evidence from a paired associate and feedback-based task[1]

Abstract

Though aphasia is primarily characterized by impairments in the comprehension and/or expression of language, research has shown that patients with aphasia also show deficits in cognitive-linguistic domains such as attention, executive function, concept knowledge and memory (Helm-Estabrooks, 2002 for review). Research in aphasia suggests that cognitive impairments can impact the online construction of language, new verbal learning, and transactional success (Freedman & Martin, 2001; Hula & McNeil, 2008; Ramsberger, 2005). In our research, we extend this hypothesis to suggest that general cognitive deficits influence progress with therapy. The aim of this experiment is to explore learning, a cognitive process that is integral to relearning language, yet underexplored in the field of aphasia rehabilitation. We examine non-linguistic category learning in patients with aphasia (n=19) and in healthy controls (n=12), comparing feedback and non-feedback based instruction. Participants complete two computer-based learning tasks that require them to categorize novel animals based on the percentage of features shared with one of two prototypes. As hypothesized, healthy controls showed successful category learning following both methods of instruction. In contrast, only 60% of our patient population demonstrated successful non-linguistic category learning. Patient performance was not predictable by standardized measures of cognitive ability. Results suggest that general learning is affected in aphasia and is a unique, important factor to consider in the field of aphasia rehabilitation.

3.1 Introduction

Traditional research in aphasia has predominantly focused on the role of brain regions specialized for language, however a growing body of lesion and neuroimaging research now recognizes that language is part of an extensive network of connected brain regions that subserve not only language, but processes such as working memory and cognitive control (Tomasi & Volkow, 2012; Turken & Dronkers, 2011). Accordingly, an increasing number of studies in aphasia rehabilitation acknowledge the important contribution of multiple factors of cognition to therapy outcomes and communicative success (Fridriksson et al., 2006; Helm-Estabrooks, 2002;

[1] Portions of this chapter were originally published as Vallila-Rohter, S., & Kiran, S. (2013). Non-linguistic learning and aphasia: evidence from a paired associate and feedback-based task. *Neuropsychologia, 51*(1), 79-90.

Keil & Kaszniak, 2002; Ramsberger, 2005). Researchers have identified skills that might be important towards constructing and retrieving language, such as attention (Erickson et al., 1996; Hula & McNeil, 2008; Lesniak et al., 2008; Murray, 2012; Peach et al., 1994), executive function (Keil & Kaszniak, 2002; Lesniak et al., 2008; Ramsberger, 2005; Zinn et al., 2007), concept knowledge (Chertkow et al., 1997) memory (Helm-Estabrooks, 2002; LaPointe & Erickson, 1991).

Along this line of work, many studies have demonstrated a disparity between language skills and non-linguistic ability (Chertkow et al., 1997; Helm-Estabrooks, 2002), illustrating that patients with aphasia can have differing degrees of impairment in both verbal and nonverbal domains. Though degrees of impairment can differ in these domains, they remain related, researchers postulating a contribution of non-linguistic cognitive impairments to the online construction of language (Hula & McNeil, 2008) and to transactional success in functional communication in aphasia (Ramsberger, 2005). In addition, some researchers have found that treatment related outcomes are best predicted by non-linguistic skills such as executive function and monitoring, rather than by language ability (Fillingham, Sage, & Lambon Ralph, 2005a, 2005b). Studies such as these draw attention to the interconnectedness of cognitive, non-linguistic factors and language, and to the importance of exploring nonverbal domains as a means of better characterizing and understanding the deficits that surface in aphasia.

We suggest that not only are nonverbal cognitive-linguistic processes important to the retrieval and construction of language in conversation, but that nonverbal *cognitive* processes might be important in the relearning or reaccess to language that is brought about through therapy. More specifically, we identify learning as a critical process involved in language relearning subsequent to stroke. Support for this hypothesis comes from recent neuroimaging studies in aphasia that explore the association between treatment related changes and neural structures and activation.

Goldenberg and Spatt (1994) for example, examined the correlation between success with therapy and lesion location and volume. Researchers found that patients who showed limited improvements in therapy had lesions that were close to, or that included portions of the entorhinal cortex, an important structure in the relay of information between the neocortex and the hippocampus (Squire, 1992) considered critical to learning and memory (Eichenbaum, Otto, & Cohen, 1992; Squire, 1992). In a functional magnetic resonance imaging (fMRI) study, Menke et al. (2009), found evidence for a relationship between short-term improvements with therapy and bilateral activation of the hippocampus, a structure critical to memory. Shortly thereafter in a diffusion tensor imaging study (DTI), Meinzer et al. (2010) showed a correlation between success with language therapy and the structural integrity of the hippocampus and surrounding fiber tracts. Studies that explore novel lexical, semantic and syntactic learning in healthy individuals have shown the engagement of similar structures (Breitenstein et al., 2005; Maguire & Frith, 2004; Opitz & Friederici, 2003) suggesting that comparable mechanisms may underlie the processes of language rehabilitation and novel learning in healthy individuals (Menke et al., 2009; Rijntjes, 2006).

While we do not know the exact mechanisms by which aphasia rehabilitation leads to functional outcomes, the findings outlined above demonstrate that the mechanisms of recovery are unlikely to be restricted to language regions alone. Therefore, we aim to use nonverbal learning in aphasia as a window into learning, proposing that a better understanding of these mechanisms could be essential in the diagnostic characterization of patients with aphasia.

As touched upon in the introductory chapter, research in other patient populations, such as Parkinson's disease, Alzheimer's disease, frontotemporal dementia and amnesia, has emphasized the importance of understanding subtleties of learning ability in patients with brain damage (Filoteo, Maddox, Ing, et al., 2005; Knowlton & Squire, 1993; Knowlton et al., 1994; Koenig, Smith, & Grossman, 2006; Koenig, Smith, Moore, Glosser, & Grossman, 2007; Shohamy, Myers, Grossman, et al., 2004) that we suggest is also essential in aphasia. One of the seminal studies drawing attention to the impact of instruction method on success with learning, conducted by Knowlton et al. (1994), explored the ability of patients with amnesia to learn stimulus outcome associations between geometric cards and weather conditions. Knowlton et al. (1994) found that an alternate means of instruction administered through gradual trial-by-trial feedback, allowed amnesic patients to overcome memory deficits and learn probabilistic card-condition pairings as well as controls. This study demonstrated that for the case of amnesia, characteristics of the to-be-learned material were not the factor confounding learning; rather, it was the method of instruction and the way in which memory systems were recruited to support learning that facilitated success.

An exploration into nonverbal learning in aphasia offers the potential to determine whether patients with aphasia experience language deficits that are supported by an intact cognitive foundation for learning, or whether deficits in language occur in the context of degraded cognitive architectures to support learning. If patients learn novel nonverbal information as well as controls, results will suggest that the observed variability in learning in aphasia is directly linked to the integrity of the language system and to linguistic demands. If, in contrast, patients with aphasia show deficits in learning novel nonverbal information, results will suggest that, in addition to cognitive-linguistic deficits, deficits in the cognitive architecture supporting general learning affect patients' abilities to learn or relearn language. If the latter is true, in the long-term, measures of nonverbal learning ability can be included into diagnostic characterizations of patients; such measures presenting a gateway towards language treatments that are selected for and/or tailored to individuals.

To this end, in the current experiment we take a nonverbal approach in the exploration of learning in aphasia and seek to determine whether patients learn novel non-linguistic tasks similarly to healthy age-matched controls. In addition, we are interested in exploring whether differences in nonverbal learning arise following different methods of instruction. For these purposes, we have developed two tasks in which participants learn to categorize novel animals as belonging to one of two categories. The two tasks have shared stimuli, and in both tasks, participants learn to categorize novel animals as belonging to one of two categories. We compare learning following instruction that is paired associate in nature and instruction administered through trial-by-trial feedback, paradigms similar in design to those implemented in aphasia (Breitenstein et al., 2004) and in healthy and brain damaged populations (Knowlton & Squire, 1993; Knowlton et al., 1994; Poldrack et al., 2001; Zeithamova, Maddox, & Schnyer, 2008).

Research has shown variable engagement of neural structures during paired associate and feedback-based categorization that interact both competitively and cooperatively (Maddox et al., 2008; Poldrack & Packard, 2003), however previous experiments suggest that trial-by-trial feedback-based learning relies heavily on cortico-striatal loops of the basal ganglia and on nondeclarative memory systems (Poldrack et al., 2001; Seger & Miller, 2010 for review). In contrast, paired associate learning in the absence of feedback is likely to have a greater dependence on medial temporal lobe declarative memory systems (Poldrack et al., 2001). While the present study does not specifically examine the neural underpinnings of feedback or paired associate learning, the behavioral manifestations following these different learning methods may be informative towards our understanding of learning in aphasia.

Based on experiments using similar tasks, we predict that healthy controls will learn categories equally well following both methods of instruction. With respect to patients, we conceive of two potential outcomes. One hypothesis is that patients with aphasia will demonstrate non-linguistic category learning that is parallel to learning observed in healthy controls. Previous studies have demonstrated that patients with aphasia are capable of new learning (Breitenstein et al., 2004; Freedman & Martin, 2001; Gupta et al., 2006; Kelly & Armstrong, 2009; Marshall et al., 1992; Tuomiranta et al., 2011), therefore in the context of non-linguistic material normal learning can be expected. On the other hand, based on research in populations with amnesia and Parkinson's disease that demonstrate disrupted nonverbal learning subsequent to brain damage, we hypothesize that patients with aphasia may also have deficits in nonverbal learning. Learning in aphasia may be attributable to both language and cognitive processing, such that patients will show impaired category learning relative to healthy controls, even when learning is non-linguistic. If this is the case, we anticipate that patients with greater impairments in executive function may show more disordered learning, as some studies have found executive function to be a predictor of therapy outcomes (Filloteo et al., 2005a, 2005b).

3.2 Materials and Methods

3.2.1 Participants. Twenty patients (ten men) with single left hemisphere strokes (*M* 61.40, *SD* = 11.98, ranging from 33.7 – 86.8 years of age) participated in the study. Upon enrollment, patients had completed between 3 and 21 years of education (*M* = 14.84, *SD* = 4.08). Patients were recruited from a patient pool at the Sargent College of Health and Rehabilitation Sciences. All patients were premorbidly right handed and were tested at least six months after the onset of their stroke. At the time of testing, patients had no concomitant medical problems. Western Aphasia Battery (WAB, Kertesz, 1982) aphasia quotients (AQs) ranged from 24.8 – 98 encompassing Broca's and Wernicke's aphasia types, Conduction, Transcortical motor and Anomic aphasia. Table 3.1 provides a breakdown of patient demographic information, aphasia type and aphasia characteristics. One patient was dropped following testing (see results) and is not included in Table 3.1. Another patient did not fully complete the WAB and therefore could not be assigned an aphasia type or aphasia quotient.

Table 3.1
Experiment 1 - Characteristics of participants with aphasia (PWA)

PWA	Age	Gender	Education	Months post onset	Aphasia Type	Comprehension	Attn.	Mem.	Exec.	VS	BNT	AQ
PWA 1	*34*	*F*	*14*	*6*	*Cond.*	*91*	*WNL*	*Sev*	*Mod*	*WNL*	*0*	*25*
PWA 2	*50*	*F*	*18*	*24*	*An.*	*185*	*WNL*	*WNL*	*WNL*	*WNL*	*100*	*94*
PWA 3	*53*	*F*	*12*	*25*	*Wern.*	*116*	*WNL*	*Sev*	*Mod*	*WNL*	*7*	*41*
PWA 4	*53*	*M*	*16*	*107*	*Cond./Wern.*	*142*	*Mild*	*Sev*	*WNL*	*WNL*	*7*	*48*
PWA 5	*61*	*M*	*13*	*6*	*An.*	*192*	*Mild*	*Mild*	*Sev*	*Mild*	*80*	*91*
PWA 6	*64*	*F*	*18*	*18*	*An.*	*143*	*Mild*	*Sev*	*Sev*	*Mild*	*13*	*68*
PWA 7	*66*	*F*	*18*	*42*	*Br.*	*120*	*Mild*	*Sev*	*Sev*	*Mild*	*0*	*28*
PWA 8	*70*	*M*	*21*	*28*	*Wern.*	*78*	*Mild*	*Sev*	*Mild*	*WNL*	*0*	*34*
PWA 9	*76*	*M*	*3*	*15*	-	-	*Mild*	*Mod*	*Mod*	*Mild*	*2*	-
PWA 10	*77*	*F*	*16*	*94*	*An.*	*200*	*WNL*	*WNL*	*WNL*	*WNL*	*98*	*98*
PWA 11	*87*	*M*	*12*	*13*	*An.*	*185*	*Mild*	*Mod*	*Mild*	*Mild*	*58*	*88*
PWA 12	49	M	12	162	Br.	137	Mild	Sev	Mod	Mild	58	58
PWA 13	52	M	11	260	An.	175	Mod	Sev	Mild	Mild	32	61
PWA 14	57	F	16	68	An.	170	Mild	Mod	Sev	Mod	57	80
PWA 15	60	M	19	27	An.	178	WNL	Mod	WNL	WNL	78	83
PWA 16	61	M	16	45	Cond.	168	WNL	WNL	WNL	WNL	43	68
PWA 17	64	F	16	65	An.	174	WNL	Mod	Mod	WNL	30	69
PWA 18	68	F	12	28	TCM	179	Mod	Sev	Mod	Sev	83	82
PWA 19	68	M	19	13	An.	74	Mild	Mild	Mod	Mild	30	74

Note. For participants with aphasia (PWA), composite scores of attention (Attn), memory (Mem), executive functions (Exec) and visuospatial skills (VS) as obtained with the CLQT, Boston naming test (BNT) scores and aphasia quotients (AQ) are reflected. Aphasia types are abbreviated as follows: conduction (Cond.), anomic (An.), Wernicke's (Wern.), Broca's (Br.) and transcortical motor (TCM). WNL indicates scores within normal limits. Italics indicate patients classified as learners during our experiment.

Table 3.2
Experiment 1 - Characteristics of control (Cn) participants

Control	Cn1	Cn2	Cn3	Cn4	Cn5	Cn6	Cn7	Cn8	Cn9	Cn10	Cn11	Cn12
Age	33	57	58	57	61	60	61	65	69	70	73	59
Gender	F	M	F	F	M	F	F	F	M	M	F	M
Education	19	16	18	16	21	19	16	12	16	16	16	18

Thirteen control participants (five men, see Table 3.2) with no known history of neurological disease, psychiatric disorders or developmental speech, language or learning disabilities took part in the study (M = 60.18, SD = 10.17, ranging from 32.9 – 72.6 years of age). One control participant was left-handed. The control group and patient group did not differ in age or in education level (mean years of education for controls = 17.00, SD = 1.91). One control participant had to be dropped after testing (see results) and is not included in Table 3.2. All participants provided consent according to Boston University's IRB. Participants received $5 for every hour of their time.

3.2.2 Stimuli. Stimuli for the experiment were two sets of 1024 cartoon animals developed by Zeithamova et al. (2008) that vary on ten binary dimensions (neck length, tail shape, feet, etc.). For each set, one stimulus was selected as prototype A with each other animal identified in terms of the number of features by which it differed from the prototype. This difference was defined as an animal's *distance* from the prototype. In other words, animals at a distance of three from the prototype all differed from prototype A by three features, and thus had seven features in common with prototype A. Only one animal differed from prototype A by all ten features (distance of 10) and was therefore selected as prototype B. In this manner two category extremes, or prototypes, were established for each stimulus set.

All animals that differed from prototype A by 1 to 4 features were then considered members of category A. These animals all shared a majority of their features with prototype A, sharing 90% to 60% of their features with the prototype as distance increased from 1 to 4, and consequently, sharing 10% to 40% of their features with prototype B. In contrast, those animals at distances 6 to 9 from prototype A were considered members of category B, as they shared 90% to 60% of their features with prototype B and only 10% to 40% of their features with prototype A (see Figure 3.1). This established two categories along a continuum, each with an internal structure related to the percentage of features shared with each of the two prototypes.

Animals were coded with a unique ten-digit string, with binary dimensions each represented as a 0 or 1. Animal 0000000000 of one stimulus set had a short neck, straight tail, pointed toes, rounded snout, pointed ears, blue color, pyramidal body, spots, downward facing head and short legs while animal 1111111111 had a long neck, curly tail, curved feet, pointed nose, rounded ears, pink color, round body, stripes, upward facing head and long legs.

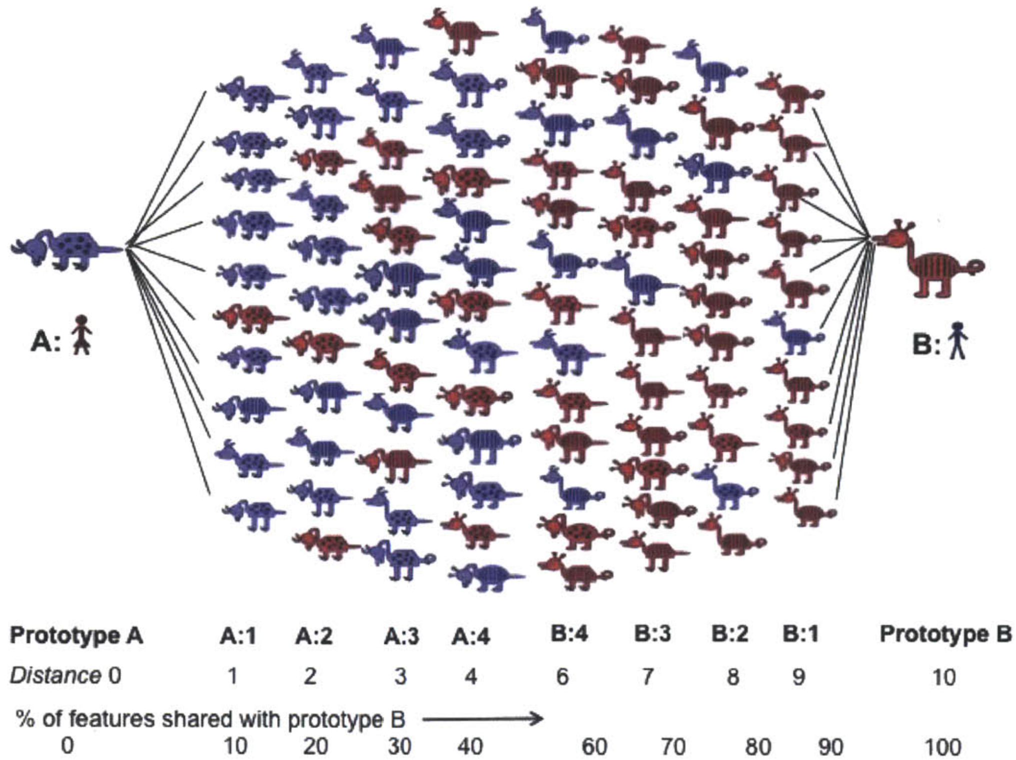

Figure 3.1: Representative animal stimuli. Sample animal stimuli contributed by Zeithamova et al. (2008). Animals are arranged according to the number of features with which they differ from each prototypical anima. The number by which an animal differs from each prototype is referred to as its *distance* from the prototype.

3.3 Design and Procedures

We used a mixed experimental design involving two groups of participants: patients and controls. Over one to two testing days, each participant completed two category learning tasks, one with paired-associate instruction and the other with feedback-based instruction. All patient participants completed the WAB, the Boston Naming Test (BNT; Kaplan, Goodglass, & Weintraub, 1983) and the Cognitive Linguistic Quick Test (CLQT; Helm-Estabrooks, 2001) in order to determine severity of aphasia and naming ability as well as to characterize patients' cognitive strengths and weaknesses.

All testing was conducted in a quiet room located at Boston University with a speech-language pathologist present to explain tasks and answer questions. At the start of each experiment, participants were instructed that they would be learning to recognize animals as belonging to one of two categories. Instructions for the category learning tasks were provided orally by the clinician with the aid of illustrated pictures. There was no limit placed on the duration of instruction so that clinicians could provide sufficient examples for patients to demonstrate comprehension of the task. Additional directions were provided orally and in writing at the start of each computerized paradigm. Learning tasks were programmed using E-Prime 2.0 (Psychology Software Tools, Pittsburgh, PA; www.pstnet.com) and consisted of a ten minute training phase involving 60 trials followed by a ten minute 72 trial testing phase. All responses were made through a computer button press. Because many patients with aphasia have compromised use of their right hand, all participants were instructed to enter responses with the middle and index fingers of their left hand. Stimulus sets and learning tasks were counterbalanced across participants.

As previously acknowledged, stimuli for the experiment were developed by Zeithamova et al. (2008). One of the experiments implemented by Zeithamova et al. (2008) provided the framework for our feedback-based task described below. The second experimental paradigm, our paired-associate task, was adapted from Poldrack et al.'s (2001) experiment in which researchers compared neural activations during paired-associate and feedback-based versions of the weather prediction task.

3.3.1 Feedback based (FB) training. In the training phase of the FB task, category A animals and category B animals were randomly presented one at a time on a computer screen. As each animal appeared on the screen, participants were given 4000 msec to guess to which of the two categories the animal belonged. Pictures and identifiers in the lower left and right corners indicated that button presses "A" and "B" corresponded to the two different categories (see Figure 3.2). After responding with a button press, participants received feedback for 3000 msec telling them the correct category and whether their response was correct or incorrect.

Training was comprised of 60 trials. Participants were trained on 20 animals that differed from each prototype by 1 to 4 features. Participants were never trained on prototypes. Trained animals were selected so that each feature appeared an equal number of times (30) during training. Features that were typical of a category (shared with the prototype) were seen 21 to 24 times associated with that category, in contrast to atypical features which were only associated with the category 5 to 9 times each. Participants were instructed to try to learn to recognize animals as belonging to one category or to another without concentrating on one particular feature. They were told that in the beginning they would be guessing entirely at random, but that through feedback and practice they would begin to learn to recognize items. A counter in the upper right-hand corner of the screen reflected the participants' percentage of correct responses with each trial. Only participants' first responses were recorded, scored and analyzed. Following the training phase, participants were tested on their ability to categorize trained and untrained items, this time receiving no feedback.

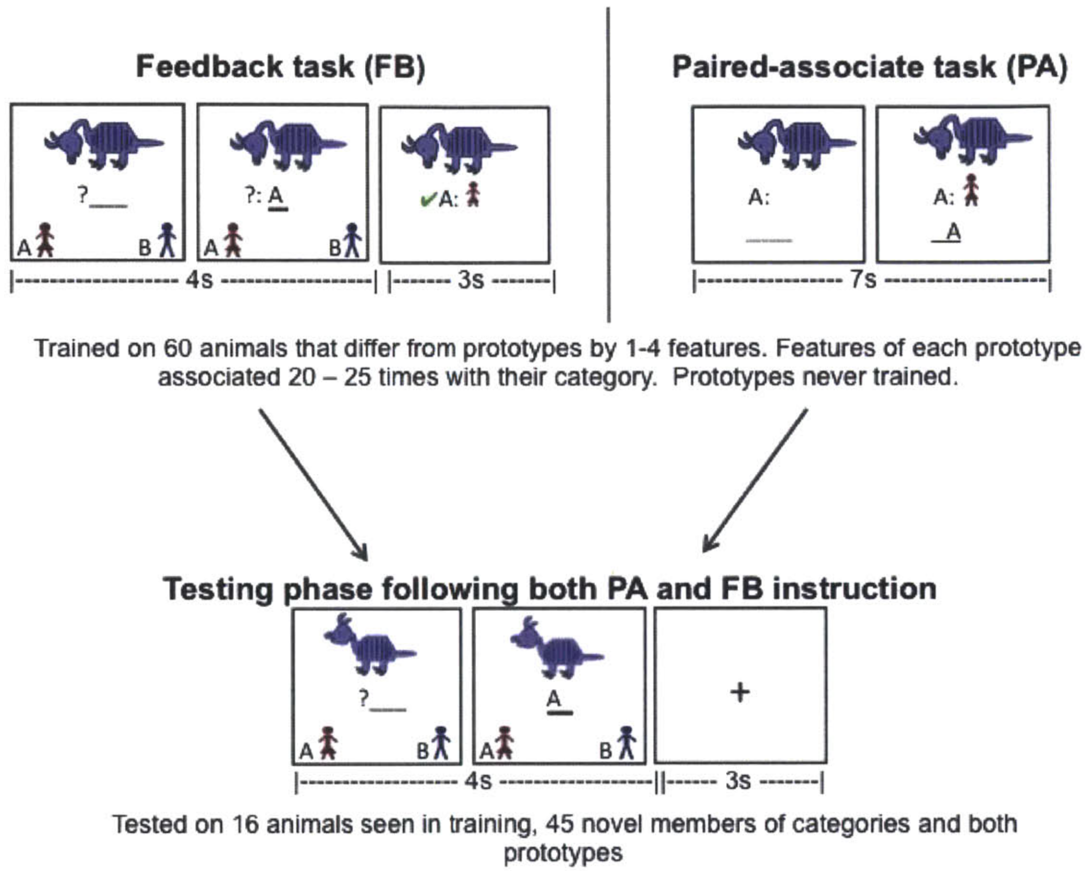

Figure 3.2: Structure of paired-associate (PA) and feedback-based (FB) instruction paradigms. Learning tasks both involved ten minute training phases followed by ten minute testing phases. During PA learning participants were provided with category labels with each stimulus presentation. During FB Learning, participants had to guess each animal's category affiliation, receiving feedback telling them whether they were correct or incorrect.

3.3.2 Paired associate (PA) training. Similar to the FB task, category A animals and category B animals were presented one at a time, however instead of learning through trial-by-trial feedback, in this paradigm each animal was presented along with a label denoting its category affiliation. Participants were instructed to press the button that matched the category affiliation as soon as they saw an animal and affiliation appear on the screen. They were told that the image would remain on the screen for a fixed number of seconds. Participants were instructed to study animals and their category labels with the goal of later recognizing animals as belonging to one category or to the other. Participants were instructed to pay attention to all of the characteristics of the animals without focusing in on one single feature.

Animals remained on the screen for 7000 msec, followed by a 1000 msec fixation cross, matching the total trial time of the FB task. Again, participants were trained on 60 animals that differed from each prototype by 1 to 4 features and were not included in the FB task, with each feature appearing an equal number of times. Prototypical animals were not shown. Features that were typical of a category were seen 20 to 25 times associated with that category, in contrast to atypical features, which were only associated with the category 5 to 10 times each. Following the training phase, participants were tested on their ability to categorize both trained and novel members of the categories.

3.3.3 Testing phases. Short testing phases that followed each training task were identically structured following PA and FB instruction (see Figure 3.2). Animals were presented one at a time on the computer screen and participants were given 4000 msec to categorize each animal as belonging to category "A" or "B". Patients received no feedback related to accuracy. If in the initial trials of a testing participants took too long to respond or did not respond, a researcher quietly encouraged them to make a button press reflective of their best guess.

Testing phases immediately followed training and were comprised of 72 trials. Participants categorized 16 animals that were seen in training, 45 novel members of the categories and both prototypes. Participants were tested on their categorization of three repetitions of prototype A and prototype B animals (6 trials), seven instances each of animals varying from prototypes A and B by 1 to 4 stimulus features (56 trials) and five midline animals varying from prototypes by 5 features (5 trials). Animals that differed from prototypes by 5 features represent the middle of the spectrum and therefore have no accurate categorization. For data analysis purposes these animals were coded with an "A" response and participants were expected to show around 50% "A" response. Data were collected on accuracy and reaction time. For the current paper, we limit our analyses to accuracy rates.

3.4 Data Analysis

One control participant and one patient participant reported attending to only one feature during categorization. Review of their data confirmed that responses favored one feature over others and were therefore dropped.

In order to ensure that no single feature had been more salient than others in its influence on responses during categorization paradigms, we completed preliminary analyses of raw data, examining the frequency with which each feature was categorized with a specific prototype. If gray color, for example, disproportionately stood out as a salient feature of category B and led participants to base their categorization on this feature alone, we would expect a greater percentage of "B" responses for those animals with the gray color feature. If all features were equivalently salient in their influence on category responses, we would expect features to be categorized with each prototype an equal number of times. Analyses confirmed that features had equal salience, the average "B" response for each feature being 54.21%, $SD = 2.55$. See Figure 3.3 for a plot of percentage of "B" responses by feature for each stimulus set.

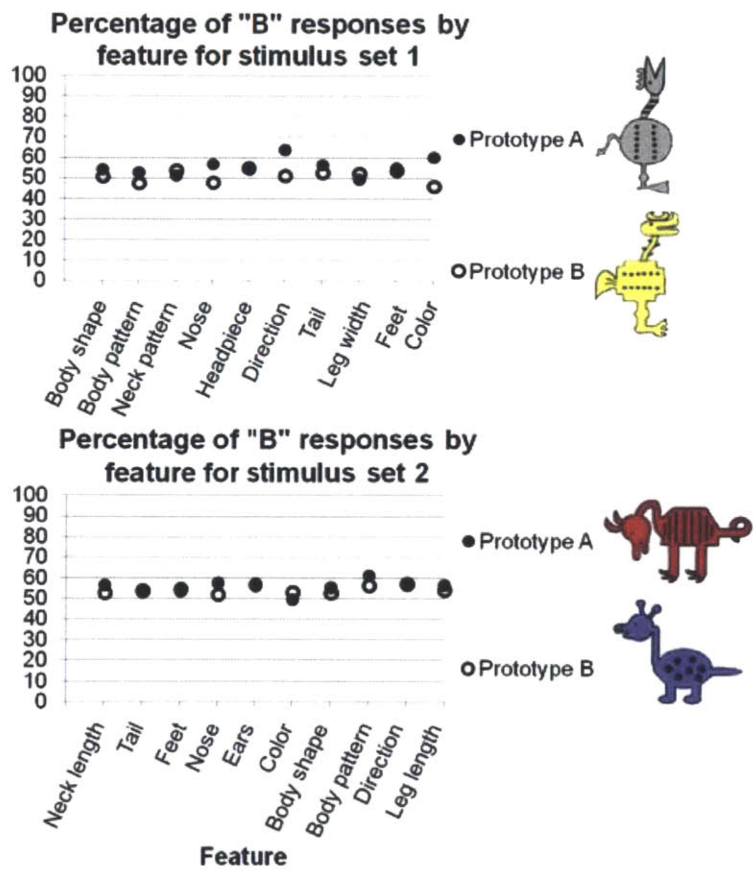

Figure 3.3: Analysis of category responses as a factor of feature dimension. Responses close to 50% represent equally salient feature dimensions. Prototypes for stimulus set 1 (upper plot) and stimulus set 2 (lower plot) shown.

Data included in further analyses were then interpreted in terms of participant ability to learn categories following the two training methods. Responses were first converted from percent accuracy score at each distance into a percent "B" response score (%BResp) at each distance. Due to the continuous, probabilistic feature structure of the two categories, we hypothesized that successful category learning would reflect internal category structure with accurate %BResp predicted to increase by a factor of 10% with each incremental distance increase from prototype A. As described in Knowlton et al. (1994), in probabilistic learning tasks, participants have a tendency to "probability match" meaning that responses will reflect the probability with which stimulus-response associations are reinforced during learning. Applied to our task, a probability match for an animal at distance 1 is hypothesized to correspond to a 10%BResp (i.e. 90% categorization with category A and 10% categorization with category B) since animals at distance 1 share 10% of their features with prototype B. Learning of our categories, therefore, is predicted to correspond to a linearly increasing %BResp with a slope of 10 (see Figure 3.4 for model prediction). Chance response would result in a 50%BResp at each distance, corresponding to a linear slope of zero.

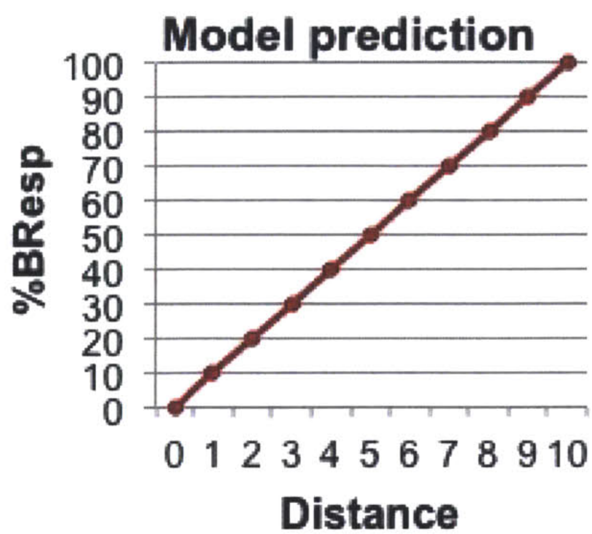

Figure 3.4: Predicted percent "B" responses (%BResp) as a function of distance. Based on the hypothesized probabilistic relationship between %Bresp and distance, successful category learning is thought to correspond to %BResp that increases linearly by a factor of 10 (slope of 10).

Overall performance was analyzed using a mixed model analysis of variance (ANOVA), with %BResp at each distance (11) and task (2 – PA, FB) as within-subject factors, and Group (2-controls, patients) as the between-subject factor. In this analysis, if overall results match our predicted model, we expect to see a significant main effect of %BResp at each distance corresponding to increasing %BResp scores with increasing ordinal distance. A significant main effect of task would suggest that average results were higher following one method of instruction over another. Similarly, higher overall scores for one group over another will result in a main effect of group. Our question of interest is to examine whether the *pattern of change* in %BResp with increasing distance differs between groups. Different patterns of change in %BResp at each distance between patients and controls (i.e. controls show increasing %BResp with increasing distance while patients show steady %BResp with increasing distance) will result in a significant group x %BResp interaction. If there is a significant interaction between task and %BResp at each distance, it would indicate that one method of instruction, FB or PA, is superior to the other.

We also conducted polynomial trend analyses at the overall participant, group and group x task levels in order to test our model linear prediction. Finally, we investigated individual results, calculating a linear correlation coefficient for each individual's data between %BResp at each distance and the ordinal variable distance. Individual results were tested for linearity using a method in which significance levels of regressions were compared when the independent variable was squared (quadratic) or cubed vs. non-squared. Results were considered linear when the non-squared regression reached significance with an alpha value <.05 and the significance of the squared term exceeded this level (Cox & Wermuth, 1994; Gasdal, 2012). We propose that if linear trends are maintained in the data, regression lines can be fitted to individual results and scores reduced to slopes; a slope of 10 representing ideal learning as described above.

3.5 Results

3.5.1 Group results. Our 11 x 2 x 2 mixed-model ANOVA with a Huyhn-Felt correction yielded a significant main effect of %BResp at each distance, $F(4.39_{\text{Huyhn-Felt corrected df}}, 290) = 30.39$, $p < .00$, matching our prediction that %BResp changed as stimulus distance from prototype A increased. There was no significant main effect of task, $F(1, 29) = 2.83$, $p = .10$, proposing that overall performance was the same for both tasks. Mean accuracy following FB instruction was 51.43% ($SD = 1.15$) compared with a mean accuracy following PA instruction of

48.89% (SD = .98). There was also no main effect of group, $F(1, 29) = .061$, $p = .81$, with mean accuracy rates of 50.35% (SD = 1.18) for controls and 49.97% (SD = .94) for patient participants. The mixed-model ANOVA yielded a significant interaction for group x %BResp at each distance, $F(4.39_{\text{Huyhn-Felt corrected df}}, 290) = 14.21$, $p < .00$, demonstrating that patients and controls showed different patterns of learning. The interaction between task x %BResp at each distance was not significant, $F(4.04_{\text{Huyhn-Felt corrected df}}, 290) = .97$, $p = .42$, demonstrating that performance did not change based on method of instruction.

The polynomial trend analysis conducted over all participant results produced a statistically significant linear trend for distance, $F(1, 30) = 63.17$, $p < .001$. No higher order trends reached significance. At the group level, polynomial trend analysis confirmed a linear relationship between %BResp and distance for the control group, $F(1, 11) = 154.60$, $p < .001$. All higher order trends were non-significant. A significant linear trend was maintained in the %BResp at each distance x task comparison, $F(1,11) = 5.18$, $p = .04$, with no significant higher order trends. A linear trend was maintained for the PA task $F(1, 11) = 634.17$, $p < .001$, as well as for the FB task, $F(1, 11) = 33.29$, $p < .001$, with non-significant higher order trends. Thus, control group results support our hypothesis that learning is reflected through a linearly increasing %BResp with increasing distance. In addition, a linear increase was observed following both FB and PA instruction.

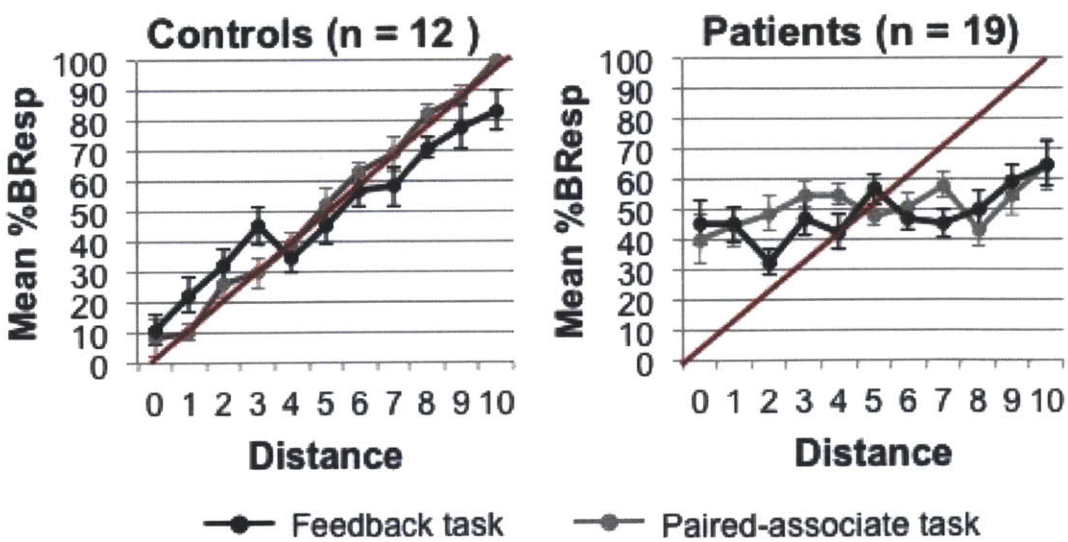

Figure 3.5: Mean scores of learning following FB and PA instruction. Plots reflect mean %BResp and standard deviations as a function of distance for control (left) and patients (right). Red lines represent predicted measures demonstrating successful learning of category structure.

For the patient group, neither linear nor quadratic trends reached significance, $F(1, 18) = 3.34$, $p = 0.08$; $F(1,18) = 1.57$, $p = .23$, respectively. Instead, results significantly matched third and fourth order trends, $F(1, 18) = 4.29$, $p = .05$; $F(1, 18) = 7.61$, $p = .01$. Polynomial trend analysis of %BResp at each distance x task did not yield any significant first, second or third order trends. Control and patient results are summarized in Figure 3.5, in plots of mean accuracy as a function of distance, in which a linearly increasing trend is apparent in the control group, while absent from patient results.

3.5.2 Individual results. Control group results matched our prediction of linearly increasing %BResp as a function of distance such that at the individual level, successful learning was defined as a significant positive correlation between %BResp and ordinal distance that also satisfied our tests of linearity.

Based on these criteria, all twelve controls demonstrated successful learning of our category tasks, with 10/12 controls showing successful learning following both methods of instruction. One additional control showed successful learning following PA instruction and FB scores that approached significance ($p = .06$). One control participant showed successful learning following PA instruction, but not FB instruction (see Table 3.3).

Among our patient group, only eleven out of nineteen patients had learning scores that satisfied our criteria for learning following at least one method of instruction (learners: PWA 1-11). In contrast, for the remaining eight patients, there were no significant positive correlations between %BResp and distance, and patterns of increase of %BResp did not follow linear trends, suggesting that these patients did not demonstrate category learning following either method of instruction (non-learners).

Closer examination of the eleven learners revealed that three were able to learn following FB instruction, but not PA instruction (PWA 1, PWA 3, PWA 11); four learned following PA instruction but not FB instruction (PWA 5, PWA 6, PWA 7, PWA 9), and three patients demonstrated control-like behavior, learning categories following both PA and FB instruction (PWA 2, PWA 4, PWA 8, see Table 3.3). One patient, PWA10, learned following PA instruction and had FB scores which approached significance ($p = .07$). Four patient learners, two of whom were classified as FB learners (PWA 1 and PWA 3) and two PA learners (PWA 6 and PWA 7) showed a pattern in which correlations between %BResp and distance were linear, and coefficients approached *negative* one (see Figure 3.6 for a representative sample of patient result plots).

Table 3.3
Individual control and patient results on PA and FB category learning tasks

	PA task					FB task					
ID	Slope	R	*p*	R^2 term	*p*	Slope	R	*p*	R^2 term	*p*	Task Learned
Cn1	9.6	1.0	***<.001	1.0	0.54	10.5	1.0	***<.001	1.0	0.11	PA & FB
Cn2	9.5	1.0	***<.001	1.0	0.08	11.6	1.0	***<.001	1.0	0.75	PA & FB
Cn3	9.2	1.0	***<.001	1.0	*0.02	8.7	1.0	***<.001	1.0	0.89	PA & FB
Cn4	8.7	0.9	***<.001	0.9	0.36	6.6	0.8	**<.01	0.8	0.48	PA & FB
Cn5	11.8	0.9	***<.001	0.9	0.46	4.6	0.6	0.06	0.6	0.83	PA only
Cn6	8.7	0.9	***<.001	0.9	0.53	9.7	0.9	***<.001	0.9	0.97	PA & FB
Cn7	11.5	1.0	***<.001	1.0	0.47	9.0	0.9	***<.001	0.9	0.83	PA & FB
Cn8	8.1	0.9	**<.01	0.9	0.71	-3.6	-0.5	0.12	0.5	0.90	PA only
Cn9	9.9	0.9	***<.001	1.0	0.05	3.1	0.6	*0.04	0.7	0.40	PA & FB
Cn10	10.6	1.0	***<.001	1.0	1.00	8.0	0.9	**<.01	0.9	*0.04	PA & FB
Cn11	8.4	0.9	**<.01	0.9	0.08	7.7	0.9	***<.001	0.9	0.89	PA & FB
Cn12	7.5	0.8	**<.01	0.9	0.31	5.9	0.7	*0.01	0.7	0.96	PA & FB
PWA 1	-9.1	-0.9	**<.01	0.9	0.71	*10.3*	1.0	**<.01	1.0	0.51	FB only
PWA 2	8.3	0.9	**<.01	0.9	0.17	*9.5*	0.9	**<.01	0.9	0.72	PA & FB
PWA 3	-9.5	-1.0	**<.01	1.0	0.76	*7.7*	0.9	**<.01	0.9	0.84	FB
PWA 4	8.0	0.9	**<.01	0.9	0.30	*9.5*	0.9	**<.01	1.0	0.33	PA & FB
PWA 5	*9.6*	0.9	**<.01	0.9	0.53	-1.9	-0.3	0.38	0.5	0.25	PA only
PWA 6	*5.2*	0.7	*0.01	0.8	0.18	-7.3	-0.8	**<.01	0.8	0.91	PA only
PWA 7	*9.8*	0.9	**<.01	0.9	0.74	-9.7	-0.9	**<.01	0.9	0.41	PA only
PWA 8	6.1	0.8	**<.01	0.8	0.98	*6.7*	0.7	*0.02	0.8	0.07	PA & FB
PWA 9	*4.9*	0.7	*0.02	0.7	0.77	2.0	0.3	0.39	0.5	0.17	PA only
PWA 10	*7.8*	0.8	**<.01	0.8	0.59	3.9	0.6	0.07	0.6	0.48	PA only
PWA 11	-0.2	0.0	0.92	0.2	0.59	*8.8*	0.9	**<.01	0.9	0.72	FB only
PWA 12	*-2.5*	-0.3	0.35	0.3	0.79	-3.3	-0.5	0.11	0.7	0.05	none
PWA 13	*1.9*	0.3	0.42	0.3	0.76	-0.5	-0.1	0.84	0.5	0.11	none
PWA 14	-4.4	0.6	0.06	0.6	0.50	*-0.8*	0.1	0.72	0.2	0.63	none
PWA 15	-1.0	-0.2	0.61	0.3	0.56	*2.3*	0.3	0.32	0.7	*0.04	none
PWA 16	*3.4*	0.5	0.11	0.6	0.41	-1.2	-0.2	0.65	0.6	0.10	none
PWA 17	-2.7	-0.3	0.33	0.6	0.10	*2.6*	0.5	0.13	0.5	0.98	none
PWA 18	*1.9*	0.3	0.31	0.4	0.62	-1.2	-0.2	0.54	0.3	0.55	none
PWA 19	-0.8	0.0	0.77	0.8	0.67	*-0.5*	-0.1	0.83	0.2	0.55	none

* $p < .05$ ** $p < .01$ *** $p < .001$

Note. Slope values in italics indicate best slope of learning identified for each patient.

We suggest that this might reflect some learning of category structure, as %BResp increased linearly by a factor of negative ten, however that categories were reversed. For this reason we remain conservative in our conclusions regarding comparisons between instruction methods. We do, however, confidently report that learning in patients with aphasia was different from learning in healthy controls, with only 60% of our patient participants demonstrating successful nonverbal category learning. Furthermore, the patterns of learning observed in the patients characterized as learners differed from the patterns of learning observed in non-learners. While those patients classified as learners showed categorical learning following at least one method of instruction as evidence by significant positive correlations between distance and %BResp as a function of distance, the eight patients who we classified as non-learners did not show significant positive *or* negative correlations between %BResp and distance following either method of instruction.

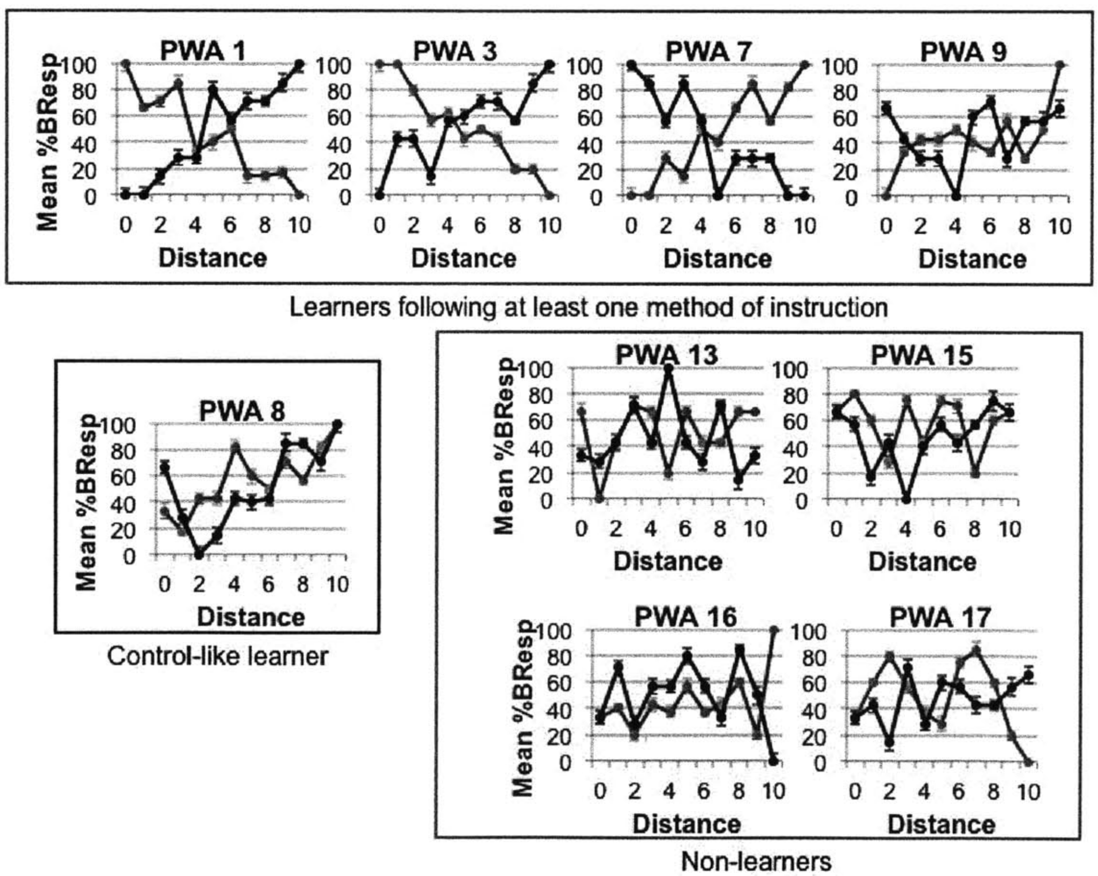

Figure 3.6: Representative sample of individual patient results. Results are presented for nine participants, grouped by learner type. Dark lines reflect FB learning and gray lines represent PA learning.

In order to interpret results relative to patient characteristics such as months post onset, aphasia type and severity to identify any predictors of learning ability, we aimed to reduce each individual patient's results into a single score. Control results demonstrated linear trends in 22/24 tests (12 participants, two tasks) and thus confirmed that for each task, %BResp at each distance was linearly related to the dependent variable and could therefore be reduced to a single score. Supported by these findings, we reduced each patient's data to two scores: one for the PA task and one for the FB task. A regression line was fitted to individual results, and slopes of regression lines were recorded. Slopes were assigned as learning scores, and were used to conduct further analyses considering the relationship between learning ability and patient profile, language and cognitive function as characterized by standardized tests. Scores for patients who did not show successful learning of our task and whose results therefore violated the assumption of linearity were still reduced. We confirmed that slopes for patient learners were closer to ten than the slopes of those patients who did not demonstrate successful learning (see Figure 3.7 for patient slope scores).

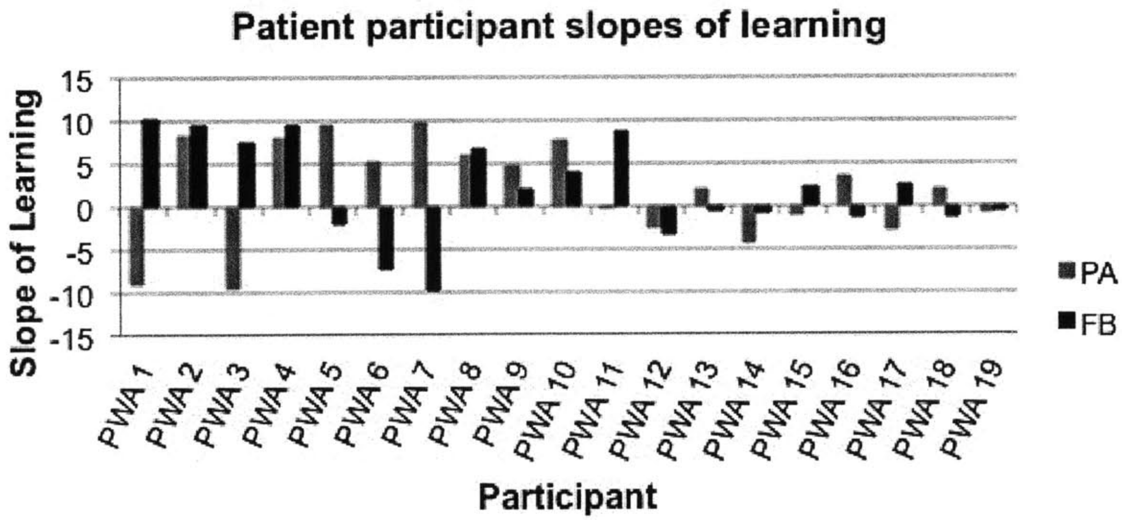

Figure 3.7: Learning slopes for each patient participant. FB scores are presented in black, PA scores in fray. Slopes closest to positive ten represent ideal learning of categories.

For subsequent interpretations of learning and patient profile we selected a "best slope" for each patient, this slope being the slope that most closely approached positive ten whether instruction was PA or FB based (see italicized values in Table 3.3). Pearson correlations of learning slopes with age and years of education were completed to explore the relationship between category learning and aphasia characteristics. We conducted additional correlations of learning slopes with aphasia quotients (AQs), raw scores on the BNT and CLQT subtests of memory, attention, executive functions and visuospatial skills.

Bivariate correlations between best slope and patient age, months post onset of stroke and years of education were non-significant. In addition, correlations between best slope of learning and BNT scores, scores of attention, scores of memory, executive function, visuospatial skills and AQs were not significant (see Figure 3.8). Visual inspection of the data demonstrated that three clusters arose among participants with respect to AQ scores. The first cluster was made up of patients who produced high scores of learning on our task and also had the most severe aphasia as characterized by AQ scores. The second cluster was comprised of patients who produced low scores of learning and had AQ scores in the middle range of severity, while the third cluster was made up of patients with high scores of learning and the highest AQ scores.

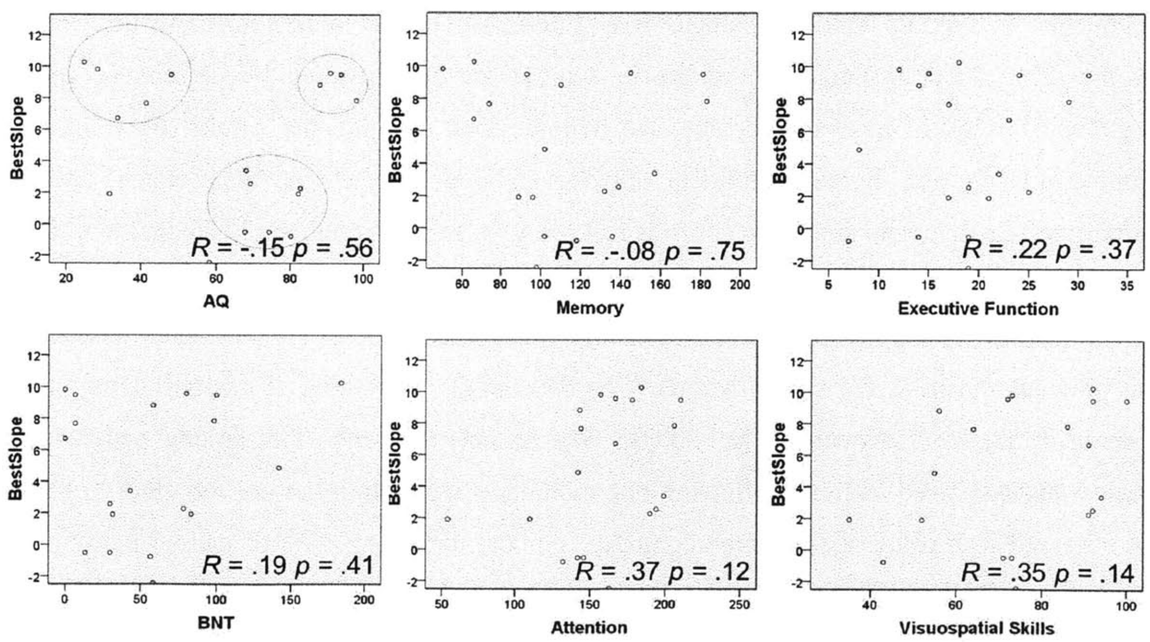

Figure 3.8: Pearson correlations between patient best slopes of learning and cognitive-linguistic measures. Correlations between best slope and AQ, BNT and scores of memory, executive function, attention and visuospatial skills as measured by the CLQT are presented. Visual inspection of the data demonstrated the presence of three clusters related to AQ scores (upper left plot).

3.6 Discussion

The aim of the first experiment of this thesis was to explore how the nonlinguistic category learning ability of individuals with aphasia compares with the learning ability of non-aphasic, age-matched controls. As hypothesized, we found that control participants were able to learn to categorize animals following both FB and PA instruction. Research exploring category learning has proposed that the process of recognizing and grouping patterns is essential in enabling our fast recognition of objects. Category learning requires individuals to process and detect commonalities across stimuli, accruing information about a series that is then organized within a framework, a process very different from single item recall or recollection (Knowlton & Squire, 1993; Seger & Miller, 2010). The current results add to the body of work that demonstrates how healthy individuals have a rapid ability to recognize and group patterns even in the absence of explicit instruction.

For the patient group, we predicted that patients with aphasia would demonstrate one of two outcomes. We hypothesized that if language deficits arise within the context of a preserved architecture to support learning, patients would demonstrate preserved non-linguistic learning. On the other hand, if language deficits in aphasia are accompanied by deficits in general cognition subsequent to brain damage, we hypothesized that patients would show impaired learning of categories. In our experiment, only eleven out of nineteen patients produced category learning results that were similar to controls following at least one method of task instruction.

For 60% of the patients with aphasia who were tested, therefore, results suggest that general learning is supported, results further implying preservation of the conceptual knowledge that provides the basis for categorization (Chertkow et al., 1997) and of categorization ability (Koenig et al., 2006; Koenig et al., 2007). We do note, however, that among patients who learned, eight showed learning following one method of instruction but not the other, a pattern not observed in healthy age-matched controls. For the remaining 40% of patient participants, impairment of general learning mechanisms or of general categorization cannot be ruled out. Together, these results show for the first time that the nature of learning new category information is impaired in stroke-related aphasia.

Concerning different methods of instruction, each posing different demands, PA and FB tasks may have presented distinct cognitive challenges for each individual patient. As noted in the introduction, the demands of feedback-based and paired-associate learning are different, feedback-based learning requiring active hypothesis generation and feedback monitoring, and typically engages corticostriatal loops; while paired-associate learning depends on the formation of associations between stimuli and outcomes through observation, and likely has a high dependence on medial temporal lobe memory systems (Poldrack et al., 2001). Differences likely impacted learning strategies, attention, monitoring and motivation of patients with aphasia while completing tasks. In spite of this, results do not suggest that one method of instruction over another provided a significant advantage for patients. Previous studies in patients with amnesia, Parkinson's Disease, Alzheimer's disease and frontotemporal dementia identified methods of instruction that significantly benefited the population tested (Filoteo et al., 2005; Knowlton et al., 1994; Koenig et al., 2006; Koenig et al., 2007; Shohamy et al., 2004) a result that was not produced in our patients with aphasia with these particular tasks and instruction methods.

For those patients who produced results with significant, but negatively correlated %Bresp with distance, we conceive that impairments at the level of response selection and execution may have played a role. Seger & Miller (2010) draw attention to the demands posed on response selection and execution during category learning, pointing to the required coordination of cognitive and motor control. We speculate that for patients who showed significant negative correlations in their results, pattern abstraction systems may be intact with deficits arising at the level of response encoding and execution. Research has confirmed that task variables such as stimulus familiarity, complexity, modality, task demands, learning situation and response mechanism contribute to distinct neural recruitment (Poldrack et al., 2001; Seger & Miller, 2010; Squire, Stark, & Clark, 2004; Zeithamova et al., 2008). Task demands have behavioral and neural implications and likely elicited damaged neural structures in our patient participants to varying degrees. Even when some learning is observed, as it was in eleven of our patients with aphasia, patients showed less consistency of learning under contrasting instruction methods, meriting further study.

Eight patients with aphasia included in the current experiment showed no learning of categorical structure following either method of instruction. In our experiment, we deemed these eight patients to be non-learners since they were unable to learn categories relative to controls, as well as relative to other patients with aphasia. We hypothesize that for these patient non-learners, learning ability is present but reduced. The current stimuli contained ten variable features and posed high processing demands. Furthermore, category boundaries were based on probabilistic associations of features with prototypes that are continuous, a design which can pose additional challenges.

Previous research has suggested that categorization of discrete stimuli can rely on automatic recognition, while continuous or complex stimuli require pattern abstraction, rule-use and feature mapping in addition to hypothesis testing (Davis et al., 2009; Love & Markman, 2003; Maddox et al., 2008; Schyns, Goldstone, & Thibaut, 1998). The pace of learning and limited trials may have provided insufficient opportunities to develop appropriate hypotheses and strategies such that some participants might have benefitted from additional training trials. While patient learners were able to overcome these complexities within the constraints of the current methods, patient non-learners may have learning systems that require additional trials, simplified stimuli, or alternate instruction methods.

Prior studies have also pointed to attention deficits in stroke (Marshall, Grinnell, Heisel, Newall, & Hunt, 1997; McDowd, Filion, Pohl, Richards, & Stiers, 2003) and many non-learners may have experienced difficulty selectively attending to appropriate stimulus features, particularly faced with complex stimuli with multiple dimensions. It should, however, be noted that learning ability was unpredictable by standardized scores of attention; three of eight non-learners scoring within normal limits on the CLQT subtests of attention. We propose that the divergence of learning ability observed in the group of patients tested relative to controls further emphasizes the need to accurately characterize learning. Many patients likely have deficits that extend beyond language and accordingly require additional support and strategies in the setting of learning. These patients may either lack some of the cognitive support systems necessary for learning, or have compromised neural systems that require additional reinforcement and focus to optimally engage neural systems during learning.

With respect to patient characteristics, language profile and learning ability, results suggest that learning ability is unrelated to demographic variables such as age, months post onset of stroke and years of education. We had predicted that learning ability might be predicted by scores of executive function. Instead, learning scores did not correlate with any of the standardized measures obtained (AQ, BNT, or CLQT scores of memory, executive function, attention and visuospatial skills). These findings are consistent with previous studies that have failed to find a predictable relationship between verbal impairments or demographic variables and skills in nonverbal domains (Chertkow et al., 1997; Helm-Estabrooks, 2002). Findings further suggest that category learning ability is distinct from skills measured by the CLQT. In the present study we aimed to explore systems that are distinct from those described through existing cognitive and linguistic tests, such that experimental results which are not fully explained by standardized assessments is not surprising.

We did note the interesting finding that upon inspection of the data, three clusters surfaced among participants based on AQs. Those patients with the lowest and with the highest AQs were most successful performing our task, while patients with AQs in the middle range were not successful at learning categories. In other words, patients with the greatest level of language impairment performed better on our learning tasks than many patients with milder deficits. Germane to this finding is the fact that standardized measures provided by the WAB and CLQT are highly language dependent. The WAB AQ is derived from measures of spontaneous speech, verbal comprehension, repetition, naming and word finding, all measures that are highly verbal. Based on our results, we posit that some patients with severely impaired language may actually have cognitive learning systems that are largely intact yet often undervalued since so many cognitive scores are dependent on language ability. The CLQT does include measures that are nonverbal such as symbol cancellation, clock drawing, symbol trails, design memory, mazes and design generation; however verbal tests requiring patients to express personal facts, retell stories, and generate names weigh heavily on composite scores of memory and attention.

Currently accepted standardized tests capture many factors that are critical to the assessment of aphasia, however it is likely that they do not fully encompass the affected systems in stroke. Results from our first experiment support the hypothesis that an additional metric of nonverbal learning ability is missing in the characterization of aphasia. As applied to a clinical setting, we propose that those patients who appear to have higher-level language skills do not necessarily present with the most intact cognitive or pattern abstraction systems. These skills are likely affected to different degrees within individuals with aphasia, contributing to our current inefficiency at predicting outcomes.

4. Experiment 2. Nonlinguistic learning in aphasia: Effects of training method and stimulus characteristics[2]

Abstract

The purpose of Experiment 2 was to further our exploration of nonlinguistic learning ability in patients with aphasia, examining the impact of stimulus typicality and feedback on success with learning. Eighteen patients with aphasia and eight healthy controls participated in this experiment. All participants completed four computerized, non-linguistic category-learning tasks. We continued to probe learning ability under two methods of instruction: feedback-based (FB) and paired-associate (PA). We also examined the impact of task complexity on learning ability, comparing two stimulus conditions: typical (Typ) and atypical (Atyp). Performance was compared between groups and across conditions. Results demonstrated that healthy controls continued to successfully learn categories under all conditions. For our patients with aphasia, two patterns of performance arose. One subgroup of patients was able to maintain learning across task manipulations and conditions. The other subgroup of patients demonstrated a sensitivity to task complexity, learning successfully only in the typical training conditions. Results further support the hypothesis that impairments of general learning are present in aphasia. Some patients demonstrated the ability to extract category information under complex training conditions, while others learned only under conditions that were simplified and emphasized salient category features. Overall, the typical training condition facilitated learning for all participants. Findings have implications for therapy, which are discussed.

4.1 Introduction

In our first experiment exploring nonlinguistic category learning in aphasia, results demonstrated that different profiles of learning arose between healthy controls and patients with aphasia. Only eleven out of nineteen patients showed learning of categories compared with across-the-board learning by control participants. Interestingly, measures of patient cognitive or linguistic abilities did not correlate with performance on learning tasks.

Many individuals with aphasia were found to be unable to learn following either FB or PA instruction. Results raised the question of whether such individuals could learn under different

[2] Portions of this chapter were originally published as Vallila-Rohter, S., & Kiran, S. (2013). Nonlinguistic learning in individuals with aphasia: Effects of training method and stimulus characteristics. *American Journal of Speech Language Pathology, 22*, S426-S437.

learning conditions or with additional trials. Thus, in the next phase of this thesis, we furthered our investigation of nonlinguistic learning, this time examining whether manipulations to stimulus complexity impacted learning in controls and individuals with aphasia.

Complexity has been the focus of considerable research in aphasia rehabilitation. Studies in aphasia have noted generalization from complex to less complex related structures, following both syntactic (Thompson, 2001, 2006; Thompson, Ballard, & Shapiro, 1998; Thompson, Shapiro, & Roberts, 1993; Thompson et al., 1997; Thompson et al., 2003) and semantic therapy (Kiran, 2007, 2008; Kiran, Sandberg, & Sebastian, 2011; Kiran & Thompson, 2003a, 2003b). This observation led to the formulation of the complexity account of treatment efficacy (CATE) hypothesis (Thompson et al., 2003), a hypothesis that draws attention to the potential impact of stimulus complexity on treatment outcomes and generalization patterns in aphasia.

Motivation for the development of CATE came from results obtained through aphasia treatment studies as well as from connectionist principles of generalization. In his influential paper, Plaut (1996) used connectionist modeling to explore patterns of relearning after damage. One experiment, focused on the impact of training typical or atypical words produced two major findings. First, the retraining simulation showed better learning overall of typical words than of atypical words. Second, and critical to the CATE hypothesis, training on atypical words resulted in substantial generalization to untrained typical words. Plaut posited that training of atypical exemplars highlighted feature variability within a category, simultaneously providing information about the breadth of categories and of central category tendencies. This breadth of information was lacking when models were trained only on typical words and resulted in limited generalization.

The goal of the current experiment was to better understand nonlinguistic category learning ability in aphasia, exploring the impacts of both stimulus characteristics and instruction method on patient success with learning. We continue to examine nonlinguistic learning ability in patients with aphasia and in healthy controls, comparing feedback-based instruction and paired associate instruction. Within these two conditions, we explore the impact of stimulus characteristics, comparing one condition in which training is designed to emphasize salient category features (typical training); and another condition in which training highlights feature variability within categories (atypical training). We will further explore whether demographic variables or standardized measures of cognitive-linguistic ability demonstrate a predictive relationship with patient scores of learning.

We hypothesize that typical training (Typ) will result in better overall learning rates than atypical training (Atyp). Based on connectionist theories, we propose that following training in the Atyp condition, participants will show generalization of learning to typical items. We hypothesize that participants may learn the Atyp condition better under feedback conditions, as research has suggested that implicit systems sensitive to feedback are better suited for complex category learning that requires information integration (Ashby et al., 2002).

4.2 Materials and Methods

4.2.1 Participants. Eighteen patients (ten men) with aphasia subsequent to single left hemisphere stroke participated in this experiment. All of the patients included in this experiment were also required to complete Experiment 1. The mean age of participants was 61.32, *SD* = 12.17 (ranging from 33.7 to 77.2 years) having completed an average of 15.83 years of education, *SD* = 2.92 (ranging from 11 to 19 years, see Table 4.1). Patients were tested at least six months after the onset of their stroke and had degrees of severity of aphasia that ranged from mild to severe at the time of testing, as determined by WAB (Kertesz, 1982) aphasia quotients (AQ, AQs from 24.8 to 98). Our patient population represented a heterogeneous sample including patients with Conduction, Broca's, Wernicke's, Transcortical Motor and Anomic aphasia, classifications determined by the WAB. All patients were premorbidly right handed and were medically and neurologically stable at the time of testing. One patient participant dropped out of the study prior to completing our diagnostic test battery and therefore is missing measures of cognitive-linguistic ability and was not assigned an aphasia type.

Eight non-aphasic control participants (three men) were also recruited to participate in this study. Similar to our patient group, all of these control participants also completed Experiment 1. Participants had no known history of neurological disease, psychiatric disorders or developmental speech, language or learning abilities. The mean age of participants was 62.87, *SD* = 6.58 (ranging from 57.2 to 72.6 years) having completed an average of 16.5 years of education, *SD* = 1.03 (ranging from 16 to 18 years, see Table 4.1). One control participant, Cn 4, was left-handed. We were most interested in patient patterns of learning and thus included only a small group of similarly aged healthy controls to serve as a baseline.

Table 4.1.
Experiment 2 - Participant information for controls (Cn) and participants with aphasia (PWA)

ID	Age	Gender	Ed.	MPO	Aphasia Type	Comp.	Attn.	Mem.	Exec.	VS	BNT	AQ
PWA 1	34	F	14	6	Con.	91	WNL	Sev	Mod	WNL	0	25
PWA 2	50	F	18	24	An.	185	WNL	WNL	WNL	WNL	100	94
PWA 3	53	F	12	25	Wern.	116	WNL	Sev	Mod	WNL	7	41
PWA 4	53	M	16	107	Con./ Wern.	142	Mild	Sev	WNL	WNL	7	48
PWA 5	61	M	13	6	An.	192	Mild	Mild	Sev	Mild	80	91
PWA 6	64	F	18	18	An.	143	Mild	Sev	Sev	Mild	13	68
PWA 7	66	F	18	41	Bro.	120	Mild	Sev	Sev	Mild	0	28
PWA 8	70	M	21	27	Wern.	78	Mild	Sev	Mild	WNL	0	34
PWA 9	77	F	16	94	An.	200	WNL	WNL	WNL	WNL	98	98
PWA 10	87	M	12	13	An.	185	Mild	Mod	Mild	Mild	58	88
PWA 11	52	M	11	260	An.	175	Mod	Sev	Mild	Mild	32	61
PWA 12	60	M	19	26	An.	178	WNL	Mod	WNL	WNL	78	83
PWA 13	61	M	16	45	Con.	168	WNL	WNL	WNL	WNL	43	68
PWA 14	64	F	16	65	An.	174	WNL	Mod	Mod	WNL	30	70
PWA 15	67	F	12	28	TCM	179	Mod	Sev	Mod	Sev	83	82
PWA 16	68	M	19	13	An.	74.3	Mild	Mild	Mod	Mild	30	74
PWA 17	48	M	16	86							82	
PWA 18	72	M	18	15	Con.	139	WNL	Mild	WNL	WNL	85	77
Cn1	58	F	18									
Cn2	58	F	18									
Cn3	57	F	16									
Cn4	60	F	16									
Cn5	69	M	16									
Cn6	70	M	18									
Cn7	73	F	16									
Cn8	59	M	16									

Note: Table of participants, age, gender, education (Ed.), months post onset of stroke (MPO), aphasia type, comprehension as determined by the WAB, attention (Att.), memory (Mem.), executive functions (Exec.) and visuospatial skills (Visusopatial) as determined by the cognitive linguistic quick test (CLQT). CLQT scores are within normal limits (WNL), mild, moderate (Mod) or severe (Sev). Scores are provided for the BNT, and AQ is a patient's aphasia quotient, an indicator of aphasia severity, higher scores representing lower degrees of impairment. Aphasia types are abbreviated as follows: Conduction (Con.), Anomic (An.), Wernicke's (Wern.), Broca's (Bro.) and Transcortical Motor (TCM).

4.2.2 Stimuli. Stimuli for the current study were the same as those included in Experiment 1 and described in section 3.2.2. For this experiment, within a category, animals that had a high feature overlap with the prototype, meaning that they had eight to nine features in common with the prototype (80% to 90% feature overlap) were considered *typical* category members. Animals that matched the prototype's features by only six to seven features (60% to 70% feature overlap) were considered *atypical* category members (see Figure 4.1).

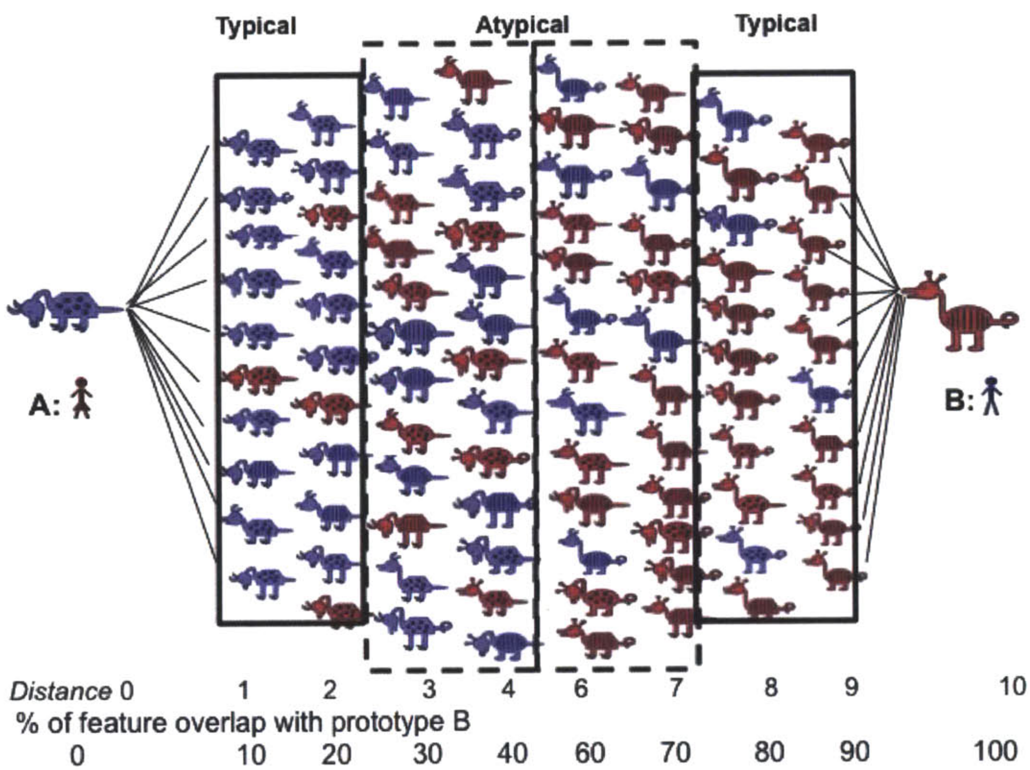

Figure 4.1: Typical and atypical animals. Typical animals share 80% to 90% of their features with prototypes. Atypical animals share 60% to 70% of their features with prototypes.

4.3 Design and Procedures.

All participants completed category learning tasks for which instruction method was either feedback based (FB) or paired associate (PA) with training items that were either typical (Typ) category members or atypical (Atyp) category members. Combining these task manipulations, four conditions were established: FB Typ, FB Atyp, PA Typ, PA Atyp. Each category-learning paradigm consisted of a ten minute training phase followed by a ten minute testing phase and is described in further detail below. As noted above, all participants also completed baseline FB and PA tasks as part of Experiment 1. Participants with aphasia completed the BNT (Kaplan, Goodglass, & Weintraub, 2001) and the CLQT (Helm-Estabrooks, 2001), standardized cognitive-linguistic assessments.

Stimulus sets and learning tasks were counterbalanced across participants, and paradigms were built such that no animal was repeatedly presented across paradigms (see Figure 4.2 for possible sequence of tests). At the start of testing, a speech language pathologist used illustrated pictures to explain tasks to participants. Participants were told that they would be completing multiple paradigms, each requiring them to learn to recognize animals as belonging to one of two families. They were informed that each task would have a similar overall structure, but that each was unique.

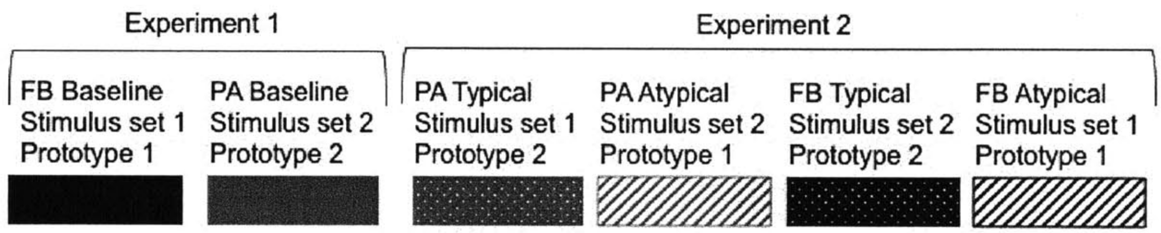

Figure 4.2: Sample sequence of testing. All participants completed baseline tasks (Experiment 1) followed by the completion of four additional category learning tasks. Task instruction, typicality, stimulus set and prototype were counterbalanced across participants.

Overall methods, total number of trials and timing for FB and PA tasks were maintained from Experiment 1. Again, for FB conditions, participants were required to guess each animal's affiliation and received feedback after each trial. In PA learning, animals were presented one at a time with a label denoting their category affiliation.

Within these parallel task structures, we constructed two training conditions: typical (Typ) and atypical (Atyp). Recall that stimuli in each category were grouped into typical animals (animals that had an 80% to 90% feature overlap with the prototype) and atypical animals (60% to 70% overlap with the prototype). Under typical training conditions, all 60 stimulus animals presented in training were typical to categories. Participants therefore saw each feature associated 24 to 30 times with one category and only 3 to 6 times with the opposite category. This condition was created in order to emphasize typical category features, increasing their salience through training.

In the atypical condition, overall task structure was maintained, the only manipulation being that the 60 stimulus animals presented in training were all atypical to categories. In this condition, participants saw features associated 15 to 21 times with one category and 9 to 15 times with the opposite category. Therefore, the atypical training condition highlighted the feature variability of categories. These paradigms are distinct from FB and PA conditions of Experiment 1, as the training phase for Experiment 1 included both typical and atypical animals.

As in Experiment 1, all training paradigms were followed by a 72-trial testing phase. Testing phases included prototypes, typical and atypical items. We were interested in examining participant abilities to learn not only animals within the training group to which they were exposed in training (typical or atypical), but whether learning generalized, such that participants showed feature matching of their responses across category items. Data were collected on accuracy and reaction time, though at this time only accuracy data are reported and analyzed.

4.4 Data Analysis

Similar to Experiment 1, mean accuracy scores at each distance from prototype A were converted into a %BResp score and responses were examined as a function of distance from prototype A. Once scores were converted to %BResp at each distance, we analyzed overall performance using a mixed model analysis of variance (ANOVA) with typicality (2 – Typ, Atyp) and instruction method (2 – FB, PA) as within-subject factors, and group (2 – controls, patients) as the between-subject factor. Main effects of group, typicality or instruction method would demonstrate that group or task manipulations impacted performance.

Next, we examined individual participant results to determine whether %BResp scores did, in fact, match the probability of feature overlap with prototype A across all distances. Linear regression coefficients and slope scores of learning were calculated for each participant in the same manner described in Experiment 1, chapter 3.4.

This model also allowed us to probe the question of generalization from atypical items to typical items following training. In order to produce %BResp scores that satisfied our conditions for learning following atypical training, participants had to produce categorizations with a high probability match for typical exemplars and prototypes. Therefore, successful learning following atypical training necessitated generalization from atypical exemplars to typical exemplars. Due to the nature of our task, where atypical exemplars have a 30% to 70% feature match with prototypes (close to chance response of 50%), we were unable to measure generalization from typical to atypical items.

Finally, we used regression analyses to explore relationships between patient slope scores of learning, demographic information and standardized cognitive-linguistic measures. Four linear regressions were run with the independent variables: age, education, and months post onset (MPO). Each of the four linear regressions had a different dependent variable: slope score following PA Typ, PA Atyp, FB Typ and FB Atyp training. Four additional linear regressions were run, this time evaluating patient slope scores of learning and standardized measures of cognitive linguistic ability. In this regression, we explored AQ, attention, memory, executive function and visuospatial skills as determined by composite scores on the CLQT.

4.5 Results

Our 2 x 2 x 2 mixed model ANOVA yielded a significant main effect of group, $F(1,23) = 14.52$, $p < .01$, demonstrating that performance on our task differed between patients and controls. There was also a significant main effect of typicality, $F(1, 23) = 11.67$, $p = <.01$, indicating that performance varied depending on whether instruction was focused on typical or atypical exemplars. The interaction between typicality and group was non-significant, $F(1, 23) = 0.46$, $p = .50$, suggesting that stimulus typicality influenced the performance of both patients and controls. There was no significant main effect of training method, $F(1,23) = 0.13$, $p = .72$. Thus, results do not suggest an advantage of one method of instruction over another, feedback-based or paired associate. Similarly, the interaction between training method and group was non-significant, $F(1, 23) = 0.32$, $p = .57$.

Patient and control slope scores for all four test conditions and for baseline conditions are reflected in Table 3.2. Recall that successful learning of categories was defined as a positive, linearly increasing %BResp with a slope approaching ten. Slope scores marked with an asterisk indicate scores that satisfied our conditions of linearity and produced significant positive regression results.

An examination of individual control results revealed that six out of eight controls were able to successfully learn categories following every method of instruction; FB Typ, FB Atyp, PA Typ and PA Atyp. One control participant (Cn 1) learned under all conditions except the PA

Atyp condition, and another control participant (Cn 4) learned only following typical training (see Table 4.2 and Figure 4.3a).

Table 4.2
Slope scores for control and patient participants on baseline conditions, Typ and Atyp training

Participant	FBBaseline	PABaseline	FBTyp	FBAtyp	PATyp	PAAtyp
Cn1	*8.70	*9.22	*7.27	*6.74	*7.84	-3.55
Cn2	*6.62	*8.74	*11.20	*8.27	*12.79	*4.46
Cn3	4.63	*11.75	*10.64	*9.59	*11.15	*8.44
Cn4	*8.96	*11.49	*10.73	-5.39	*11.21	4.31
Cn5	*7.96	*10.56	*9.91	*9.68	*9.35	*7.47
Cn6	*7.71	*8.40	*8.45	*10.43	*12.25	*9.57
Cn7	*5.89	*7.53	*8.48	*9.89	*11.26	*9.63
Cn8	*10.52	*9.61	*7.58	*7.59	*9.44	*8.98
Pt 1	*10.26	-9.07	*10.41	*10.84	*10.10	-8.29
Pt 2	*9.48	*8.29	*8.75	*6.73	*9.61	-1.04
Pt 3	*7.66	-9.46	*9.89	*10.11	*9.719	*9.59
Pt 4	*9.48	*7.96	*8.48	-5.96	*10.74	-6.60
Pt 5	-1.9	*9.57	*9.35	-1.5	0.06	*9.35
Pt 6	-7.32	*5.15	0.88	-5.96	*8.01	*8.48
Pt 7	-9.74	*9.81	*10.00	*8.98	-10.11	*9.00
Pt 8	*6.71	*6.06	*10.21	1.07	-4.03	4.26
Pt 9	1.95	*4.87	*10.52	*9.09	*11.21	*8.01
Pt 10	3.94	*7.84	*5.14	2.08	*4.74	8.27
Pt 11	-3.33	-2.45	*11.39	**6.10	*6.88	-4.61
Pt 12	-0.52	1.91	*9.72	2.48	*8.79	-1.99
Pt 13	-0.78	-4.37	*10.23	-5.76	3.92	1.69
Pt 14	2.27	-1.04	-0.96	0.76	*11.47	1.86
Pt 15	-1.17	*3.4*	-2.36	-4.08	-7.42	
Pt 16	2.55	-2.66	*7.58	-2.93	-1.77	2.77
Pt 17	-1.17	*1.93*	*10.61	-6.21	*9.61	-7.51
Pt 18	-0.52	-0.76	*10.61	-6.212	3.333	*8.29

Note: Slope scores indicated with an asterisk satisfied our conditions of linearity and also produced positive significant regressions with ordinal distance from prototype A. These slopes represent successful learning of categories.

Upon examination of individual patient results, we found that nine out of eighteen patients with aphasia were able to learn categories under at least one atypical training condition (See Table 4.2 and Figure 4.3b). All nine of these patients were also able to learn categories successfully following at least one typical training condition, FB or PA. We examined the performance of these patients on Experimental task 1 and found that of the nine patients who learned following at least one atypical training condition, six also demonstrated successful learning of at least one baseline task.

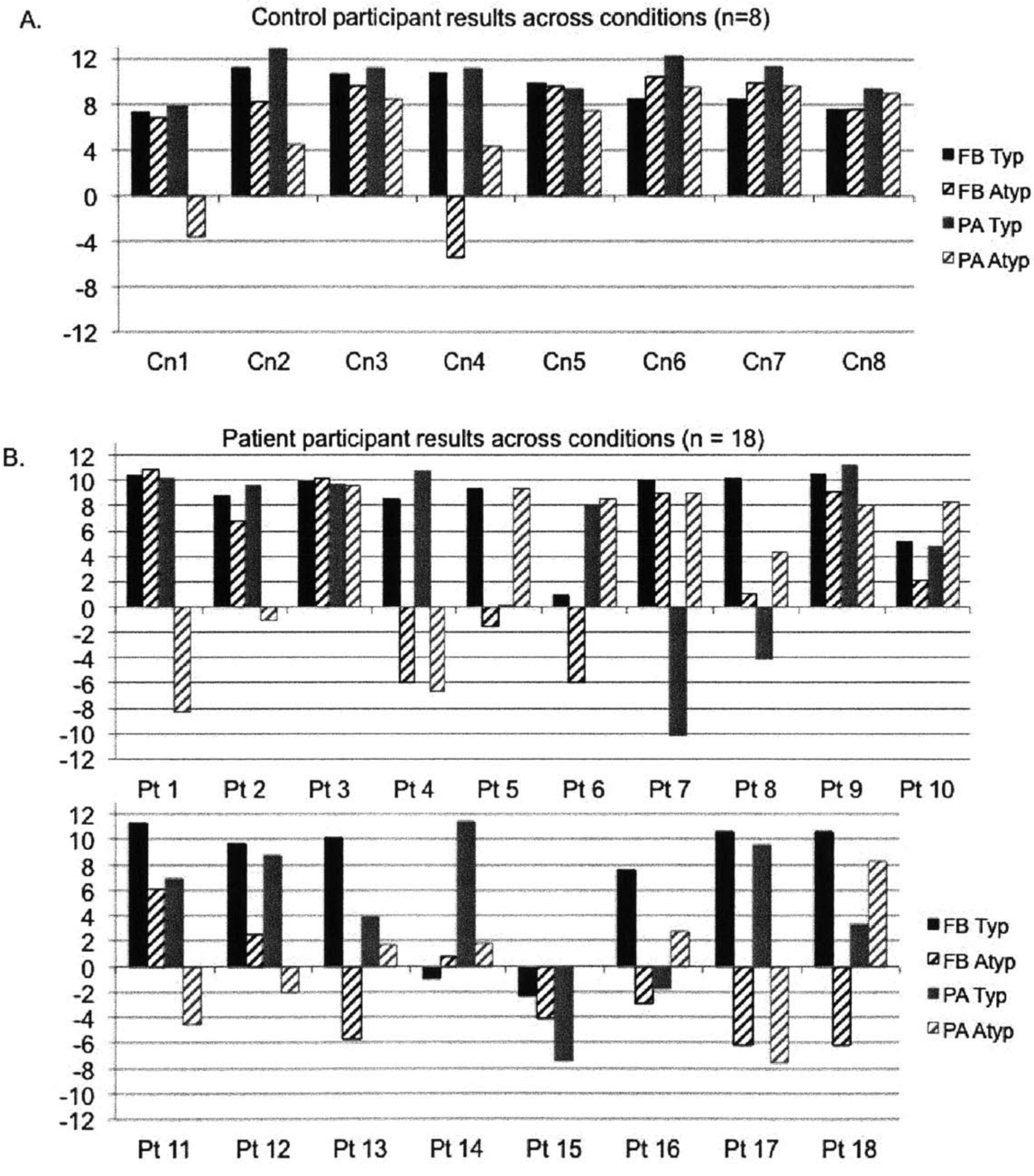

Figure 4.3: Slope scores of learning across tasks. Panel A shows results for control participants. Panel B shows results for patient participants. The horizontal line indicates the lower bound for scores that satisfied learning conditions of linearity and significant regression between %BResp and distance.

Of the nine remaining patients who did not learn following atypical training, eight were able to learn under at least one typical training condition, FB or PA. Among these patients, only three were able to successfully learn baseline tasks from our previous experiment, suggesting an overall more limited ability to extract central category tendencies from training items that contain category variability. For these patients, learning occurred primarily under conditions that emphasized feature overlap between categories.

Regression analyses exploring patient learning scores (slopes) with demographic measures produced only one significant relationship. Age was significantly related to slope scores on the PA Atyp condition ($p<.01$, see Table 4.3). Results from all other regressions of demographic measures and slope scores of learning in PA Typ, PA Atyp, FB Typ and FB Atyp conditions were non-significant. Similarly, all linear regressions between slope scores and cognitive-linguistic measures of AQ, attention, memory, executive function and visuospatial skills were non-significant (see Table 4.3).

Table 4. 3

Regression results exploring slope scores and patient demographic and linguistic variables

Dependent Variable	Independent Variable	B	Standard Error (of B)	β	Significance
PA Typ	Age	-0.19	0.14	-0.35	0.18
	Education	-0.08	0.59	-0.04	0.89
	MPO	0.02	0.03	0.17	0.52
PA Typ	AQ	-0.24	0.18	-0.97	0.21
	Attention	-0.02	0.10	-0.16	0.85
	Memory	0.17	0.12	1.19	0.18
	Executive Function	0.18	0.51	0.19	0.73
	Visuospatial	-0.06	0.26	-0.23	0.82
PA Atyp	Age	0.36	0.09	0.69	**<0.01
	Education	-0.53	0.41	-0.23	0.22
	MPO	-0.04	0.02	-0.38	0.06
PA Atyp	AQ	0.24	0.15	1.05	0.14
	Attention	0.12	0.09	1.05	0.21
	Memory	-0.10	0.01	-0.78	0.35
	Executive Function	-0.32	0.47	-0.35	0.51
	Visuospatial	-0.15	0.25	-0.57	0.56
FB Typ	Age	-0.09	0.09	-0.27	-0.30
	Education	0.38	0.38	0.26	0.33
	MPO	0.02	0.02	0.25	0.36

FB Typ	AQ	-0.17	0.10	-1.10	0.13
	Attention	-0.04	0.06	-0.45	0.56
	Memory	0.08	0.07	0.87	0.27
	Executive Function	0.22	0.30	0.37	0.46
	Visuospatial	0.02	0.15	0.12	0.90
FB Atyp	Age	-0.09	0.13	-0.18	0.50
	Education	-0.40	0.58	-0.19	0.51
	MPO	0.00	0.03	0.01	0.97
FB Atyp	AQ	-0.06	0.17	-0.27	0.72
	Attention	0.06	0.10	0.55	0.52
	Memory	-0.04	0.11	-0.27	0.75
	Executive Function	0.56	0.48	0.63	0.26
	Visuospatial	-0.12	0.25	-0.50	0.63

** $p < .01$

4.6 Discussion

In this study, we extended our previous examination of learning ability through an investigation into the impact of training method and stimulus characteristics on the non-linguistic category learning ability of patients with aphasia and a control group of healthy individuals. We compared feedback based and paired associate instruction on a multi-dimensional category learning task; conditions which researchers have posited might differentially engage learning systems through the course of learning. We posited that patients would learn better under feedback-based conditions, as researchers have found improved information integration learning under feedback conditions (Ashby et al., 2002).

For both our patients with aphasia and our healthy controls, at the group level learning ability was similar under paired associate and feedback-based conditions. Thus, for our task, there was no observed advantage of feedback over observational training. Our task differed from the task implemented in Ashby et al. (2002) by stimulus type and categorical rules. Training manipulations may have had a less significant impact on strategy use in our task than it did in the Ashby et al. (2002) study.

Results suggest that when patients with aphasia are able to successfully learn categories, they can do so under either PA or FB conditions. These findings are in line with results from Experiment 1. Though studies conducted in other patient populations with brain damage have suggested that feedback-based and paired associate instruction significantly impact learning ability (Ashby et al., 2002; Ashby et al., 2003; Ell, Weinstein, & Ivry, 2010; Knowlton, Mangels, et al., 1996; Knowlton et al., 1992; Maddox, Ashby, Ing, & Pickering, 2004; Maddox et al., 2008), this was not the case for our patients with aphasia examined as a group. In Parkinson's disease and in amnesia, brain regions critical to feedback-based and paired associate learning, basal ganglia structures and medial temporal lobe structures respectively, are the known foci of lesions. Therefore, the observed behaviors and sensitivity to the presence or absence of feedback are supported by characteristics of the underlying neural damage. While our experiments 1 and 2 do not reveal which strategies are used by patients with aphasia, results suggest that patient are able to select appropriate strategies whether instruction is paired associate or feedback-based. Diverse methods of instruction exist that have not yet been systematically explored in aphasia, and may merit further study. The diversity of lesions and profiles in aphasia may require ideal instruction methods to be identified on an individual basis.

Our second factor of interest, stimulus typicality, did impact performance on our category learning tasks. Overall, we found that the typical training condition facilitated learning for all participants. All controls learned under typical training conditions and seventeen out of eighteen patients were able to learn following typical training. These findings are supported by Plaut's (1996) work that noted that connectionist networks relearned trained items faster when exposed to typical category exemplars than when trained on atypical category exemplars. Plaut proposed that typical training conditions highlight salient category features, limiting the complexity of training.

Regarding atypical training conditions, we first found that most control participants showed successful category learning in this condition. Successful learning following atypical training requires accurate categorization of typical items; therefore data from six control participants demonstrate support for connectionist principles that suggest that highlighting feature variability provides not only information about category breadth, but also about central category tendencies (Plaut, 1996). The majority of control participants were able to successfully extract category information in a short period of time despite high task demands. For one control (Cn4), we hypothesize that the atypical training condition was too complex for her to extract category information successfully following such a limited number of trials. For this control, learning was limited to the typical training condition in which salient category features are emphasized.

For our patient participants, only 50% were able to extract central category tendencies following training that highlighted feature variability. Examination of their results on baseline tasks showed that most of these patients also learned under baseline conditions of Experiment 1. We propose that these patients have robust category learning mechanisms that allow them to recognize and track patterns efficiently. For the remaining patients tested, category learning was only successful under the typical training condition. These patients did not demonstrate the ability to extract central category tendencies from atypical training items, and in addition, generally did not successfully learn under Experiment 1, baseline conditions. Thus, for seven of eighteen patients, learning was only successfully achieved when instruction highlighted feature overlap within categories. For these patients, an emphasis on central category tendencies proved critical to successful learning. We propose that for these patients, general mechanisms of learning are impaired, successful category learning occurring only under conditions that are facilitative and simplified.

In our examination of the relationship between demographic and cognitive-linguistic variables and learning scores, only age and slopes scores in the PA Atyp condition were significant. The severity of deficits, as characterized by the WAB aphasia quotient did not predict patient success with our task, suggesting that performance on our task is not directly related to severity of aphasia. We hypothesize that the aphasia-inducing strokes that each of our patients participants experienced may have differentially affected learning and language networks. Some patients may have severe language deficits within the context of a relatively persevered system for category learning while others experience mild language deficits within a more significantly impaired category learning network.

One might also hypothesize that patients had different premorbid learning abilities. Though for the majority of our control group learning was consistently maintained across conditions, controls may have engaged learning strategies differently to perform the various tasks. Explicit and implicit learning systems are described to compete or interact throughout learning (Ashby & Valentin, 2005; Cincotta & Seger, 2007; Poldrack et al., 2001; Moody et al., 2004; Seger & Miller, 2010). Healthy individuals may engage the learning system that is most efficient for them despite varying task demands.

Clinically, results demonstrate differential category learning abilities among patients with aphasia. Category learning depends upon the ability to detect and integrate commonalities or patterns and is considered essential towards helping us rapidly recognize and classify objects meaningfully (for review see Ashby et al., 1998; Ashby & Maddox, 2005; Keri, 2003; Seger & Miller, 2010). Current results suggest that post-stroke some patients may have difficulty engaging in such integrative processes. We do not suggest that these patients lose the ability to learn categories entirely. Our task engaged participants in very short phases of learning of complex information. It is conceivable however, that many patients with aphasia may experience difficulty in the process of integrating commonalities across stimuli.

We propose that patients who experience difficulty integrating commonalities during our task might also have difficulty integrating commonalities during therapy. Thus for these patients, therapies focused on simple targets and simple tasks that reinforce salient patterns and strategies are likely to be the most effective means of promoting improvement. Patients with general learning mechanisms that are not well suited for extracting central category tendencies, likely do not have language learning mechanisms well suited for extracting central category tendencies.

In contrast, we suspect that patients with a demonstrated ability to extract commonalities under conditions that highlight feature variability will translate these skills to therapy. These patients likely have general learning mechanisms suited to integrate variability and abstract patterns, mechanisms which can be recruited in therapy. We propose that these patients would be suitable candidates for therapies which include complex, variable tasks and targets.

We are limited in our predictions, as the current study involved a limited group of patients with heterogeneous profiles of aphasia. Also, we can only infer that skills demonstrated on our non-linguistic category learning task will translate to performance in actual language therapy. The next step will be to test whether predictions drawn from short, controlled non-linguistic tasks can translate to progress with therapy.

5. Experiment 3. Learning ability as a predictor of successful outcomes with language therapy in post-stroke aphasia[3]

Abstract

One of the major challenges in the field of aphasia rehabilitation is the problem of predictability of outcomes. Studies have begun to point to a combination of cognitive-linguistic factors as potential predicting factors. In Experiment 3 of this thesis, we examine the relationship between abstract category-learning ability and progress with language therapy. Thirty-seven individuals with chronic aphasia completed the nonlinguistic category learning paradigms outlined in Experiment 1. Individuals were also enrolled in ten weeks of structured language therapy. Effect sizes in therapy were compared with measures of learning ability as well as with standardized demographic and cognitive-linguistic measures. Scores of feedback-based learning paired with years of education was found to be the best model predictor of outcomes with language therapy. No standardized cognitive-linguistic measures correlated with performance in therapy. Analyses also demonstrated that instruction method impacted strategy use when performing category-learning tasks. Results confirm the hypothesis that non-verbal learning phenotype is positively associated with treatment outcomes. We propose that many skills necessary for non-linguistic learning (hypothesis formation, feedback monitoring) likely play an important role in the relearning or re-accessing of language brought about through therapy.

5.1 Introduction

As described in the introduction, one of the major issues that clinicians and researchers continue to be faced with in aphasia rehabilitation is the problem of predictability of outcomes with therapy. Early research demonstrated that the severity of language impairment and lesion size present important predictors of spontaneous recovery (Goldenberg & Spatt, 1994; Pedersen et al., 2004; Plowman et al., 2012). In the phases of aphasia rehabilitation, however, time after time patients with similar degrees of language impairment show variable responses to treatment (Conroy et al., 2009; Fillingham et al., 2006; Hickin et al., 2002; Lambon Ralph et al., 2010). While current therapies are selected based on extensive tests that characterize language

[3] Portions of this chapter have been submitted for publication and are currently under review as Vallila-Rohter, S., & Kiran, S. (under review). Learning ability as a predictory of successful outcomes with language therapy in post-stroke aphasia.

impairments in individuals, these tests are not sufficient in predicting patient responses to therapy. The field remains in great need of improving the predictability of outcomes following language rehabilitation.

For many years, the general rehabilitation literature has pointed to cognitive factors as important factors in patient progress with therapy (Galski, Bruno, Zorowitz, & Walker, 1993; Mysiw, Beegan, & Gatens, 1989; Novack, Haban, Graham, & Satterfield, 1987; Robertson, Ridgeway, Greenfield, & Parr, 1997). Factors such as abstract thinking, sustained attention and judgment have proven to be successful predictors of recovery and outcomes post-treatment (Mysiw et al., 1989; Novack et al., 1987; Robertson et al., 1997). These skills are thought to be important skills for learning and functional carry-over of rehabilitation skills into real life (Galski et al., 1993).

Such findings from general rehabilitation have begun to influence the factors examined in studies of targeted language treatments in aphasia. Increasingly, researchers are exploring a broad range of standard assessments of cognitive-linguistic function when trying to identify predictors of outcomes. In most cases, standardized measures of language alone do not suffice to predict outcomes. Instead, researchers are finding that cognitive assessments or a combination of cognitive-linguistic assessments most consistently surface as measures significantly correlated with therapy gains (Conroy et al., 2009; Fillingham, Sage, & Lambon Ralph, 2005; Fillingham et al., 2006; Fillingham, Sage, & Ralph, 2005; Goldenberg & Spatt, 1994; Hinckley, Patterson, & Carr, 2001; Lambon Ralph et al., 2010; Seniow, Litwin, & Lesniak, 2009; van de Sandt-Koenderman et al., 2008).

Fillingham et al., (2005a, 2005b, 2006) for example, completed a three-part study examining the effects of an anomia treatment using errorful and errorless learning paradigms, exploring outcomes as they related to patient profiles of cognitive-linguistic ability. In all three studies, patients were found to progress equally well following errorless and errorful methods. In two of the studies, no measure of language ability correlated with observed therapy outcomes (Fillingham et al., 2005a, 2006). Instead, therapy gains most closely correlated to non-language scores of recognition memory skills (Fillingham et al., 2005a, 2006), the test of self-rating, thought to represent monitoring skills (Fillingham et al., 2005a, 2005b, 2006), and the Wisconsin Card Sorting Test (WCST), thought to reflect executive skills (Fillingham et al., 2005a, 2005b, 2006). Researchers hypothesized that therapy protocols likely required executive skills, memory and attention, as patients integrated and tracked feedback (errorful condition), or as they learned through Hebbian principles of increased strength through exposure (errorless condition).

In another treatment study, this time focused on anomia treatment using phonemic and orthographic cueing, Lambon Ralph et al., (2010) examined the treatment progress of 33 individuals with aphasia, comparing outcomes with a battery of standardized cognitive-linguistic assessments. Pearson correlations between post-treatment naming results and cognitive-linguistic measures produced six significant correlations. Three of these were with tests of language ability measuring naming (BNT), semantic memory (three picture Pyramids and Palm Trees test; PAPT) and reading ability (Psycholinguistic Assessments of Language Processing in Aphasia; PALPA, oral reading: imageability x word frequency subtest). The remaining three significant correlations were with cognitive tests of attention (The Test of Everyday Attention elevator counting with distraction), and tests thought to require perceptive analysis, memory, attention, planning and working memory (Rey Figure Copy and Rey Figure delayed recall). Results further confirmed the importance of assessments of non-linguistic cognitive ability in the evaluation of patients as well as in the development and selection of appropriate therapies for individuals.

Experiments 1 and 2 demonstrated that patients with aphasia exhibit variable patterns of learning ability on our category learning tasks. Observed patterns have led us to postulate that patterns of learning might reflect behaviors in therapy. In Experiment 3, therefore, we examine the relationship between nonlinguistic category learning ability and rehabilitation outcomes. We have proposed that learning ability should be included in the diagnostic characterization of patients with aphasia (see Figure 5.1). Via this experiment, we explore whether it is realistic to propose that a task as abstract as our category-learning task might relate to treatment outcomes.

Though this is the first time that skill learning has been explored as a predictor of therapy in stroke-related aphasia, learning ability has been probed in other fields (Uprichard, Kupshik, Pine, & Fletcher, 2009; Watzke, Brieger, Kuss, Schoettke, & Wiedl, 2008). In a longitudinal study of learning potential and rehabilitation in patients with schizophrenia, Watzke et al., (2008) found a positive association between measures of learning potential and long-term rehabilitation outcomes. Researchers used a modified version of the Wisconsin Card Sorting test administered in three phases to classify patients as high scorers, learners or non-learners. Researchers found that learning ability rating related to performance during rehabilitation as well as to performance in follow-up three months later. Researchers proposed that learning represented a means of measuring a patient's potential to respond to intervention. Traditional assessments focus on quantifying strengths and weaknesses. Assessments of learning quantify *potential,* independent of baseline level of functioning.

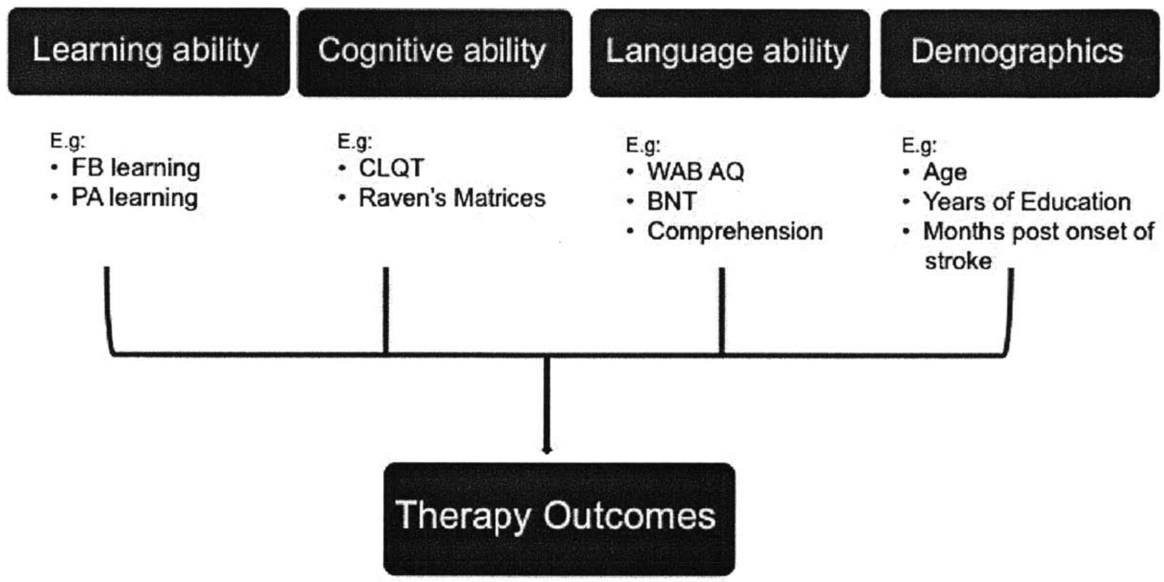

Figure 5.1: Potential predictors of language therapy outcomes

Uprichard et al., (2009) applied a similar approach in a study of outcomes and community integration in a group of individuals suffering from acquired brain injury. Learning potential was assessed following completion of the Wisconsin Card Sort Task with instruction and feedback. Researchers found that scores of learning on this task predicted the degree of patient integration into the community following treatment. Researchers again suggested that learning ability reflected potential for improvement. They found a measure of potential to be superior in predicting outcomes, compared with static measures that characterized strengths and deficits at a specific point in time.

In this experiment, individuals with aphasia were enrolled in theoretically based language therapy that engaged patients in metalinguistic instruction related to thematic role assignments and sentence meaning. Participants also completed FB and PA category-learning paradigms to assess their learning ability on our structured task. A therapy based on thematic role assignments and sentence meaning was selected as the focus of this experiment as it likely requires many of the complex skills of stimulus tracking, hypothesis generation and feedback monitoring necessary for successful feedback-based category learning. We hypothesize that scores of learning will relate to outcomes with therapy in aphasia, such that better learners produce greater improvements in language ability following a 10-week language therapy protocol. We predict that individuals with relatively poor scores of learning will show more limited improvements following therapy. We compare learning ability scores under FB and PA conditions.

5.2 Methods

5.2.1 Participants. Thirty-six individuals with aphasia (21 men) due to left hemisphere stroke, ages ranging from 33.7 to 86.8 participated in this experiment (mean age = 60.5, *SD* = 11.6). Thirty-four participants were pre-morbidly right handed and suffered from a left hemisphere stroke. Two participants were left-handed prior to their right-hemisphere aphasia-inducing stroke.

Severity of aphasia, as determined by aphasia quotients (AQs) computed from the WAB (Kertesz, 1982) ranged from 10.2 to 98.0 (mean AQ = 71.3, *SD* = 23.2). Aphasia types included Global, Broca's, Wernicke's, Conduction, Transcortical motor and Anomic aphasia as determined by the WAB. Though the WAB classifies AQ scores under 92 as abnormal, individuals with higher AQs were included in our study as they were judged to have aphasia by a clinical speech-language pathologist. In addition, they all demonstrated deficits in comprehension on our therapy screeners making them eligible for therapy. Participants were tested at least six months after the onset of their stroke (the individual in the most chronic stage of his aphasia was 260 months post onset of stroke). All participants were English speaking and two were bilingual speakers of English and Spanish. See Table 5.1 for participant information. Participants were recruited from the Boston area and tested at the Sargent College of Rehabilitation Sciences.

Table 5.1
Experiment 3 - Participant characteristics and scores

ID		Age	AQ	Aphasia Type	Comp	BNT	Attn	Mem	Exec	VS	Raven	MPO	Ed	FB	PA	ES
PWA1	M	49	58	Broca’s	52	58	163	98	19	74	49	162	12	-3.3	-2.5	-1.2
PWA2	M	52	62	Anomic	61	32	54	96	21	52	27	260	11	-0.5	1.9	-0.3
PWA3	M	53	58	Wernicke's	49	72	125	108	11	57	86	48	16	-6.5	0.9	-0.1
PWA4	F	68	82	TCM	53	83	110	89	17	35	43	28	12	-1.2	1.9	0.6
PWA5	F	63	69	Anomic	43	30	194	139	19	92	92	65	16	2.6	-2.7	0.6
PWA6	M	60	83	Anomic	73	78	190	132	25	91	92	27	19	2.3	-1.0	1.3
PWA7	M	54	93	Anomic	74	80	193	143	27	96	81	115	16	2.1	6.0	1.4
PWA8	M	61	91	Anomic	89	80	167	145	15	72	57	6	13	-1.9	9.6	2.1
PWA9	M	46	73	Broca's	55	82	195	118	30	99	92	86	16	0.4	0.6	2.3
PWA10	F	77	98	Anomic	84	98	206	183	29	86	92	94	16	3.9	7.8	2.6
PWA11	F	57	80	Anomic	61	57	132	118	7	43	51	68	16	-0.8	-4.4	3.0
PWA12	M	72	77	Wernicke's	56	85	173	132	21	83	57	15	18	-0.6	0.4	4.0
PWA13	M	44	96	Anomic	79	95	196	151	27	96	95	12	12	5.8	-5.4	4.9
PWA14	M	61	68	Conduction	56	43	199	157	22	94	--	45	16	-1.2	3.4	8.7
PWA15	M	68	74	Anomic	53	30	142	136	19	73	68	13	19	-0.5	-0.8	9.8
PWA16	F	50	94	Anomic	86	100	210	181	31	100	92	24	18	9.5	8.3	11.5
PWA17	M	76			--	2	142	102	8	55	--	15	3	2.0	4.9	0.0
PWA18	F	34	25	Wernicke's	--	0	184	66	18	92	27	6	14	10.3	-9.1	8.2
PWA19	M	53	91	Anomic	89	47	72	113	23	56	78	24	16	1.5	6.3	7.1
PWA20	M	59	86	Anomic	65	82	196	148	26	95	89	28	12	2.8	0.8	1.4
PWA21	F	83	93	Anomic	70	95	172	145	22	79	78	39	16	-7.5	2.6	1.7
PWA22	F	58	88	Anomic	61	97	178	144	20	80	65	65	16	-0.8	-4.4	3.0
PWA23	F	74	51	TCM	51	17	38	113	14	38	59	14	12	0.3	-6.1	3.0
PWA24	F	55	85	Anomic	67	90	192	152	26	88	73	10	12	2.5	9.9	1.2

PWA25	M	59	78	Conduction	52	83.3	194	156	40	92	100	110	16	9.3	9.6	6.3
PWA26	M	65	23	Wernicke's/ Conduction	53	6.67	197	93	28	101	--	120	16	8.5	8.7	-1.5
PWA27	F	66	70	Conduction	48	62	184	120	20	88	65	84	18	7.8	-6.5	0.0
PWA28	M	87	88	Anomic	68	58	143	110	14	56	51	13	12	8.8	-0.2	0.4
PWA29	M	53	48	Wernicke's/ Conduction	61	7	178	93	24	92	65	107	16	9.5	8.0	1.5
PWA30	F	64	68	Anomic	52	13	146	102	14	71	68	18	18	-0.5	-3.4	4.7
PWA31	F	53	41	Wernicke's	53	7	144	74	17	64	35	25	12	7.7	-9.5	5.9
PWA32	M	70	10	Global	46	0	13	30	3	17	38	76	12	10.0	-3.5	9.8
PWA33	F	66	31	Broca's	48	0	101	40	3	39	31	42	18	-9.7	9.8	5.8
PWA34	M	66	86	Anomic	52	73	--	--	--	--	--	123	16	8.7	-10.0	0.5
PWA35	F	38	78	Anomic	71	55	173	139	22	77	57	53	16	10.3	-0.2	3.1
PWA36	M	68	95	Anomic	97	77	192	155	28	97	95	21	17	6.4	-7.0	3.5

PWA indicates participant with aphasia
F indicates female; M male
Comp indicates comprehension score as determined by therapy screening batteries. Bilingual patients do not have this measure.
Attn, Mem, Exec, VS indicate scores of attention, memory, executive functions and visuospatial skills as determined by the CLQT
Ed indicates years of education
FB and PA indicate slope scores on category learning tasks

5.3 Design and Procedures.

All participants completed standardized assessments of their cognitive-linguistic ability. The WAB was administered to assess language abilities and determine ratings of aphasia severity. Four participants completed only part of our assessment battery and therefore have incomplete scores (see Table 5.1). The BNT (Kaplan et al., 2001) was administered to gather information about naming ability. The CLQT (Helm-Estabrooks, 2001) was administered to characterize cognitive strengths and weaknesses. All participants completed learning tasks as described in Experiment 1, chapters 3.2 and 3.3. Participants were enrolled in therapy as described in further detail below.

5.3.1 Language therapy. Prior to being included in the treatment portion of the study, each participant completed a screening measure to assess auditory comprehension of the nouns and verbs that would be included in treatment and monitoring batteries. Participants also completed a sentence comprehension screener to assess their auditory comprehension of the multiple sentence structures included in therapy. Individuals were assigned a baseline score of sentence comprehension based on their performance on this screener. Screening procedures and detailed stimulus information are available in Kiran et al. (2012). After completing screening measures, participants were enrolled in a sentence comprehension treatment involving one to two hour sessions with a clinician two times a week.

5.3.1.1 Stimuli. Stimuli for language therapy were object relative (OR), object cleft (OC), passive (PA) or unaccusative (UNACC) sentences (see Kiran et al., 2012). Stimulus pictures were drawn for each sentence depicting the action of the sentence. Foil pictures were created which contained the same nouns and actions of the sentence with altered thematic roles. Paper dolls were also created representing the nouns contained in each sentence. Sentences contained an equal number of animate and inanimate nouns.

5.3.1.2 Design. A single subject, multiple baseline design was used (Thompson, 2006). Prior to initiating therapy, participants completed three baselines. During these baselines, individuals were presented with 75 sentences, which included 10 to 15 tokens of their trained sentence type and 60 to 65 tokens of alternative sentence types. Once treatment was initiated, weekly monitoring batteries were administered. Four different versions of each monitor were created and versions were counterbalanced across baselines and throughout the course of therapy.

Individuals were trained on fifteen to twenty OR, OC, PA or UNACC sentences in therapy. Therapy protocols were designed to explicitly emphasize thematic role assignment. In the first step of therapy, the clinician read the target sentence aloud and asked the participant to indicate his/her interpretation of the sentence. Individuals with aphasia either indicated their understanding using two presented pictures, one depicting the action of the sentence and the other its foil with alternate thematic role assignment; or by manipulating paper dolls that represented constituents of target sentences. Feedback regarding accuracy was provided. The clinician then provided additional explanations regarding the roles of agent and theme while focusing on the target picture or manipulating paper dolls.

This therapy protocol was selected, as it is metalinguistic in nature requiring patients to think about thematic role assignments as they relate to sentence meaning. Patients had to attend to complex auditorily and visually presented information, receive and integrate feedback across sessions. The two bilingual participants were enrolled in a therapy with a different structure, but which posed similar auditory, visual processing and feedback integration demands.

Therapy continued for ten weeks or until participants reached 80% accuracy on monitoring batteries for two consecutive weeks. After treatment was terminated, participants completed three additional post-treatment monitoring batteries. All baseline, treatment and monitoring sessions were video recorded and scored by the treating clinician. Reliability was performed by an unbiased student trained to code responses and adherence to treatment protocol.

A therapy effect size (ES) was calculated for each participant by subtracting the average of all post-treatment baseline scores from the average of all pre-treatment baseline scores. This value was then divided by the standard deviation of pre-treatment baselines (Beeson & Robey, 2006).

5.4 Data Analysis

All participant category-learning data were analyzed and assigned a score of learning. Prior to calculating learning scores for each individual, as completed in Experiment 1, raw data were examined to ensure that participants did not base responses on one feature alone. In order to do this, we looked at responses to every animal based on feature, examining the percentage of B responses made for each feature value. Individuals with close to a 100% response rate for one feature value (e.g. circular body) and close to 0% response rate for the alternate feature value (e.g. square body) were judged to be basing responses on one feature. Using this method, we found that eleven participants attended to only one feature during training or testing. In every case, this occurred in the FB condition. Because instructions emphasized attending to multiple animal features during learning and categorization, our primary analyses focus only on those participants who demonstrated attention to multiple animal features during categorization (n = 25; PWA1 to PWA25). As individuals who attended to only one feature in FB training (n=11; PWA26 to PWA36) showed an interesting pattern of FB versus PA behavior, we retained their data for secondary analyses.

Next, to determine whether there was a relationship between learning score and treatment outcomes, we examined the correlation between learning slopes and ES in treatment. We were also interested in determining whether other measures related to outcomes and therefore examined correlations between ES in treatment and scores on our battery of standardized cognitive-linguistic assessments. Individual Pearson correlations were run between ES and AQ, BNT, scores of attention, memory, executive function, language and visuospatial skills as determined by the CLQT, and Raven's matrices. Additionally, we examined the correlation between ES and demographic variables of age, months post onset (MPO) and education. Analyses were first run on our main subgroup of twenty-five individuals. Follow-up analyses examined results from the eleven participants who were found to attend to only one feature during learning.

5.5 Results

5.5.1 Main participant subgroup. The average participant slope scores of learning following FB instruction for the twenty-five participants in our main subgroup was 2.7, SD = 5.33. FB learning scores ranged from -9.7 to 10.3. The average slope score of learning following PA instruction for these participants was 0.69, SD = 6.01. PA learning scores ranged from -9.9 to 9.9. Average effect size scores following language therapy for these patients was 3.2, SD= 3.35. Effect size scores ranged from -1.2 to 11.5. Both learning ability and effect size exist along a continuum and therefore a range is to be expected.

Pearson correlations between treatment ES and our FB slope of learning produced a significant correlation. The correlation between ES and learning slope in the PA condition was non-significant. Pearson correlations between ES and cognitive-linguistic measures of aphasia severity, naming, comprehension, attention, memory, visuospatial skills, executive functions, and Raven's matrices abilities all produced non-significant correlations (see Table 5.2, Figure 5.2). Thus FB learning slope was the only measure that significantly correlated with ES in treatment.

We then explored the relationship between ES in language treatment and demographic variables of age, education and MPO. Results were only significant between ES and years of education (see Table 5.2, Figure 5.2).

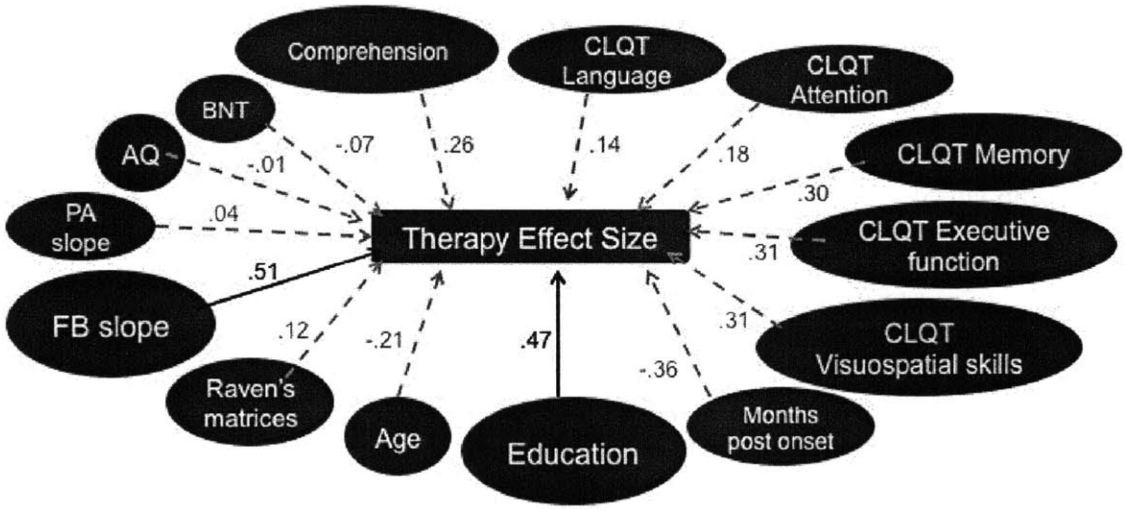

Figure 5.2. Schematic representing correlation strengths between potential contributors to therapy outcomes and effect size in treatment. FB slope and years of education were the only significant correlations with effect sizes.

Table 5.2
Correlation results for main group between effect size in treatment and cognitive-linguistic and demographic measures

Variable	N	r	p value
FB slope	25	0.51	0.01*
PA slope	25	0.04	0.83
AQ	24	-0.01	0.98
BNT	25	-0.07	0.73
Comprehension	23	0.26	0.24
CLQT Language	24	0.14	0.51
CLQT Attention	25	0.18	0.38
CLQT Memory	25	0.3	0.15
CLQT Executive function	25	0.32	0.12
CLQT Visuospatial skills	25	0.31	0.13
Raven's Matrices	23	0.12	0.59
Age	25	-0.21	0.32
Education	25	0.47	0.02*
Months post onset	25	-0.36	0.07

* p < .05

Multiple regressions were run to determine the best predictors of effect size in treatment. A two-variable model including feedback slope and education was found to be the best model predictor of effect size in language treatment $F(2,22) = 9.22$, $p = .001$, $R2 = .45$. This model accounted for 41.6% of the variance in the data. Both variables added statistically significantly to the prediction, $p < .05$. Scores of months post onset, executive function, memory and visuospatial skills, the measures with the next highest correlation values, did not contribute significantly to the prediction.

5.5.2 Subgroup of patients who attended to only one feature in FB learning. We next examined cognitive-linguistic measures and aphasia types among our subgroup of individuals who attended to only one feature during treatment to determine whether cognitive-linguistic differences arose between this subgroup and our main group of individuals. Independent samples t-tests demonstrated two significant differences. Our subgroup of eleven participants was found to have significantly lower average BNT scores than the main group, $t(33) = 3.1$, $p < .01$. Average scores of memory as measured by the CLQT were also significantly lower for this group, $t(33) = 2.95$, $p < .01$. Measures of aphasia severity approached a significant difference, with the subgroup having overall lower AQ scores, $t(33) = 2.04$, $p = .06$. Raven's matrices scores also approached a significant difference, $t(33) = 1.8$, $p = .08$. No significant between-group differences arose in measures of comprehension, attention, executive function or visuospatial skills. Interestingly, overall treatment effect sizes did not differ between groups, $t(34) = .21$, $p = .83$.

Non-parametric Spearmen correlations were evaluated between ES, cognitive-linguistic and learning measures due to the smaller size of this group. Spearmen correlations between ES and scores of attention and visuospatial skills both produced a significant relationship in the negative direction. Individuals with high scores of attention and those with high visuospatial scores produced low ES scores in treatment. The correlation between ES and measures of executive function approached significance. Spearman correlations between ES and all other standardized cognitive-linguistic measures as well as with FB and PA slopes produced non-significant results (see Table 5.3).

Table 5.3
Correlation results for subgroup between effect size in treatment and cognitive-linguistic and demographic measures

Variable	N	r	p value
FB slope	11	-0.19	0.57
PA slope	11	-0.18	0.59
AQ	11	-0.34	0.3*
BNT	10	-0.51	0.13
Comprehension	11	-0.26	0.45
CLQT Language	9	-0.38	0.32
CLQT Attention	10	-0.71	0.02*
CLQT Memory	10	-0.52	0.12
CLQT Executive function	10	-0.61	0.06
CLQT Visuospatial skills	10	-0.68	0.03*
Raven's Matrices	9	-0.47	0.2
Age	11	-0.06	0.86
Education	11	-0.13	0.7
Months post onset	11	-0.39	0.23

$p < .05$

5.6 Discussion

The aim of this experiment was to explore the relationship between measures of learning ability on our nonlinguistic category learning task and effect size following a structured language therapy program. In experiments 1 and 2, we identified variability among patterns of learning in individuals with aphasia. Thus, in the current experiment, we were interested in exploring the relationship between category-learning ability and success with therapy. We aimed to examine whether measures of learning and/or a combination of standardized cognitive-linguistic measures might serve as superior predictors of outcomes with therapy.

Results demonstrated that for this particular therapy paradigm, no standardized linguistic or cognitive measure correlated with effect size following treatment. This finding is not surprising, as many studies have failed to identify correlations between success in therapy and established cognitive-linguistic measures (Fillingham et al., 2005a, 2006). We do acknowledge that our cognitive-linguistic battery was not exhaustive and that standardized tests may exist that correlate with success with therapy. In the current thesis however, we have tried to focus on tests that are frequently reported in the aphasia literature, and on those tests that have previously been implicated as having a relationship with language therapy outcomes.

We hypothesized that scores of category learning would be related to participant outcomes with therapy and found that the only measure that correlated with effect size was our slope measure of learning following feedback-based instruction. The FB condition of our learning task engaged individuals in gradual trial-by-trial feedback learning which likely relies on many networks and skills as individuals integrate visual information, track stimulus-response associations and select strategies (Cincotta & Seger, 2007). Feedback processing, rule learning, hypothesis testing, switching and tracking are likely integral to this form of learning (Filoteo & Maddox, 2007). We propose that such skills were also likely important for the successful completion of our sentence comprehension treatment.

In therapy, individuals with aphasia were asked to attend to auditorily presented information while looking at pictures or dolls. After making a response, individuals received feedback, integration of which was integral to success with therapy. In addition, individuals with aphasia received metalinguistic instruction related to thematic role assignments as they related to sentence meaning. Successful progress with therapy required attending to multiple facets of instruction while integrating multiple inputs. This type of complex integration likely involves many cognitive skills such as attention, executive function, monitoring and integration working in unison. While these skills may individually be captured by the CLQT to certain degrees, we propose that our feedback-based learning task likely requires simultaneous use and balance of these skills in a complex way. FB learning ability may thus more accurately characterize the integrity of skills needed for successful progress with therapy.

Regression analyses demonstrated that the best model predicting performance in therapy combined measures of FB learning with years of education. For this therapy paradigm in particular, education may have related to participant exposure and familiarity with complex sentence structures. Education and learning ability may also be related and both contribute to the way in which patients engage in and approach therapy.

Results from this experiment demonstrate that a link can in fact be made between abstract nonverbal tests and language therapy. Though many facets of learning and language therapy remain to be explored, current findings validate the hypothesis that nonverbal category learning is informative for therapy. These results serve as a first indication that nonverbal learning phenotype is positively associated with therapy outcomes.

6. Experiment 4. Strategy use and category learning in individuals with aphasia

Abstract

In experiment 3 we observed that a subgroup of participants with aphasia attended to only one feature during FB instruction but not PA instruction. Prior research has suggested that clinical populations implement distinct strategies to perform probabilistic learning tasks and that these strategies may reflect processing strengths and deficits. As a result, we developed experiment 4, an experiment in which we examine the strategies implemented as controls and individuals with aphasia complete probabilistic category learning tasks. We compare strategy use following instruction that is feedback-based versus paired-associate. Results demonstrate that controls and patients with aphasia engage a variety of strategies when completing feedback-based category learning. While the majority of controls engaged optimal or suboptimal strategies, nearly half of our patients with aphasia did not engage an effective strategy following feedback-based instruction and produced poor overall learning scores. In contrast, the paired-associate version of our task led nearly all participants to engage a random pattern of responses. Results confirm that individual variability arises not only in category learning ability, but in the strategies implemented to complete category learning tasks. Method of instruction has a significant impact on the strategy implemented during learning and is likely important for learning during language therapy.

6.1. Introduction

One of the factors that remains unexplored in aphasia is strategy use, the means with which individuals carry out learning when presented with a task. Many aphasia therapies work towards retraining language through manipulations of auditory and visual stimuli, feedback, and modeling. Currently, we are limited in our understanding of how patients approach such tasks. Are patients attending to all stimuli presented during therapy, or are they focusing on one modality or one stimulus item at a time? Are individuals actively integrating feedback and constructing hypotheses related to instruction and cueing? Are patients able to devise strategies to carry over what is learned in therapy into real-world communicative scenarios? All of these are questions relevant to therapy, whose answers lie in a better understanding of the ways in which patients with aphasia process information while they are engaged in therapy tasks.

Thus, in the current experiment, we aim to better understand how information is processed during learning through an exploration into strategy use during probabilistic category learning. While this represents a unique approach in aphasia, recent studies in other populations have examined strategy use. Research has suggested that distinct strategy use likely influences individual performance on probabilistic learning tasks, and may better explain the differential results observed in clinical subgroups (Gluck et al., 2002; Hopkins, Myers, Shohamy, Grossman, & Gluck, 2004; Meeter et al., 2006; Meeter et al., 2008; Rustemeier, Schwabe, & Bellebaum, 2013).

Of particular relevance to the current experiment for its methods and findings, Gluck et al. (2002) explored strategy use while healthy participants undertook learning of the weather prediction task (WPT, briefly described in chapter 1.3.1). In the first phase of their study, interview and multiple-choice questions proved to be unreliable indicators of strategy selection. Researchers therefore, devised quantitative methods to evaluate strategies. Three model strategies were proposed: multi-cue, one-cue and singleton. Multi-cue strategies were those in which responses matched the probabilistic association of individual cards and also of combinations of cards. Singleton strategies were defined as strategies in which outcomes only matched the probabilistic association of individual cards (not card combinations). One-cue strategies were defined as responses based on the presence or absence of a single cue card (Gluck et al., 2002; Shohamy, Myers, Onlaor, et al., 2004). Behavioral responses of 60 subjects completing 200 classification trials were compared with expected data predicted from each model. In an analysis over all trials, researchers found that the majority of participants engaged singleton strategies. Analyses over blocks of 50 trials however, demonstrated that most individuals actually engaged in a mix of strategies. Many started with a simple, singleton strategy before shifting to complex multi-cue strategies in the last blocks of training. Overall, researchers concluded that there are many ways to approach the WPT; healthy individuals exhibiting use of a variety of strategies and/or shift in strategies during learning.

Since this pioneering work, other researchers have applied similar methods towards strategy analysis, furthering our understanding of probabilistic learning (see Meeter et al., 2008 for review). Meeter et al., 2006 applied strategy analysis to previously published data involving controls and individuals with amnesia (Hopkins et al., 2004). Researchers incorporated a "random" strategy into these analyses that corresponded to random patterns, switching strategies or probablistic rules not captured by other models. Researchers observed a pattern similar to that observed by Gluck et al., (2002) in which control participants shifted from a reliance on simple strategies to complex ones through the course of learning. In contrast, individuals with amnesia were found to rely on simple strategies, or no strategy throughout learning. Researchers hypothesized that individuals with amnesia were impaired in their ability to recall attempted strategies and consolidate feedback during learning.

Another study recently explored strategy use under two different instruction conditions: feedback-based versus observational learning (Shohamy, Myers, Grossman, et al., 2004). Under these conditions, researchers compared performance between healthy controls and a group of individuals with Parkinson's Disease (PD). Results demonstrated that 1) individuals with PD were impaired relative to controls under feedback-based learning conditions, 2) individuals with PD showed a heavier reliance on singleton strategies than controls in feedback-based conditions and 3) strategy use greatly differed between feedback-based and observational learning conditions. Specifically, while most participants were either fit by multi-cue or singleton cue strategies under feedback-based learning conditions; the majority of participant results were not consistent with any strategies previously described by Gluck et al. (2002) following observational learning. Findings highlighted the fact that different instruction methods led to distinct strategy implementation. Furthermore, one method of instruction was found to be superior in promoting learning for PD patients. As PD patients have known basal ganglia dysfunction, researchers concluded that striatal and midbrain dopaminergic regions are critical to feedback processing in probabilistic category learning. Researchers hypothesized that observational versions of this probabilistic learning task were likely supported by medial temporal lobe declarative memory systems, a finding consistent with previous neuroimaging research (Poldrack et al., 2001).

The sum of these studies draws attention to the insights that can be brought about through an examination of strategy use during learning. Furthermore, they demonstrate how distinct task conditions can elicit distinct performance and strategy use. Therefore, in the current experiment, we analyze strategy use in a group of patients with aphasia and a group of healthy controls as they complete probabilistic category learning tasks. We continue to compare conditions in which training is feedback-based versus paired-associate (observational). We apply an adaptation of Gluck et al. (2002) and Meeter at al.'s (2006) mathematical models to determine whether individuals engage an optimal multi-cue strategy (OMC), various singleton cue strategies (SC) or a random pattern (RP) during classification following training phases.

In our experimental paradigm, instructions specifically emphasized attending to multiple features at once. We therefore suspect that the majority of our participants will enlist OMC strategies during learning following feedback-based instruction. As previous studies have observed a shift from SC to OMC strategies through the course of learning, we do suspect that the shorter nature of our task may lead to an increased reliance on SC strategies. Based on prior research that has identified impairments in strategy switching in populations with brain damage, we predict that more participants with aphasia will rely on SC strategies than controls.

6.2. Methods

6.2.1. Participants. Forty-six patients (29 men) with aphasia due to stroke, ages ranging from 28.4 to 86.8 (mean age = 60.6, *SD* = 11.9) participated in the study. Patients completed an average of 15.3 years of education, *SD* = 3.1. Severity of aphasia, as determined by AQs computed from the WAB (Kertesz, 1982) ranged from 10.2 to 98.9. Aphasia types included Global, Broca's, Wernicke's, Conduction, Transcortical motor and Anomic aphasia as determined by the WAB. Patient cognitive-linguistic abilities were tested using the CLQT (Helm-Estabrooks, 2001). Patients were tested at least six months after the onset of their stroke (the patient in the most chronic stage of his aphasia was 260 months post onset of stroke). All patients were English speaking and two patients were bilingual speakers of English and Spanish. Two patients were premorbidly left handed and suffered from right-hemisphere stroke. One patient was premorbidly left handed and suffered from left-hemisphere stroke. The remaining patients were right handed and had aphasia subsequent to a left-hemisphere stroke. See Table 6.1. for patient information. Patients were recruited from the Boston area and tested at the Sargent College of Rehabilitation Sciences. One participant dropped out of the study prior to completing the non-feedback based version of the category learning task.

A group of twelve non-aphasic control participants (4 men) also completed the experiment. These individuals were matched in age with the group of patients with aphasia (mean age = 61.27, *SD* = 2.95) ages ranging from 32.9 to 83.1 years. Controls were also matched to the average years of education of the patient group (mean years of education = 16.2, *SD* = 2.95). Control participants had no known history of neurological disease or developmental disabilities. One control participant was left-handed. These controls are the same controls included in experiment 1 (see Table 3.2). All participants completed FB and PA learning tasks as described in experiment 1, Chapter 3.3.

Table 6.1
Experiment 4 - Patient participant characteristics, slope scores and implemented strategy

	Age	AQ	AphasiaType	BNT	Attn	Mem	Exec	VS	MPO	Edu
PWA1	52	61	Anomic	32	54	96	21	52	260	11
PWA2	53	58	Wernicke's	72	125	108	11	57	48	16
PWA3	67	82	TCM	83	110	89	17	35	28	12
PWA4	63	69	Anomic	30	194	139	19	92	65	16
PWA5	61	91	Anomic	80	167	145	15	72	6	13
PWA6	46	72	Broca's	82	195	118	30	99	86	16
PWA7	57	80	Anomic	57	132	118	7	43	68	16
PWA8	72	77	Wernicke's	85	173	132	21	83	15	18
PWA9	61	68	--	43	199	157	22	94	45	16
PWA10	68	74	Anomic	30	142	136	19	73	13	19
PWA11	76	--	--	2	142	102	8	55	15	3
PWA12	53	91	Anomic	47	72	113	23	56	24	16
PWA13	59	86	Anomic	82	196	148	26	95	28	12
PWA14	73	91	Anomic	77	46	142	16	32	136	19
PWA15	66	97	Anomic	65	200	142	29	101	15	12
PWA16	58	88	Anomic	97	178	144	20	80	65	16
PWA17	74	50	TCM	17	38	113	14	38	14	12
PWA18	55	85	Anomic	90	192	152	26	88	10	12
PWA19	75	83	TCM	90	144	114	10	62	17	16
PWA20	28	86	Conduction	78	202	156	30	100	23	18
PWA21	59	74	Conduction or Anomic	23	131	113	6	52	48	16
PWA22	87	88	Anomic	58	143	110	14	56	13	12
PWA23	50	94	Anomic	100	210	181	31	100	24	18
PWA24	58	78	Conduction	83	194	156	40	92	110	18
PWA25	69	34	Conduction or Wernicke's	0	167	66	23	91	27	21
PWA26	60	99	Anomic	98	209	175	32	101	70	16
PWA27	34	25	Wernicke's	0	184	66	18	92	6	14
PWA28	68	95	Anomic	77	192	155	28	97	21	17
PWA29	56	87	Anomic	83	196	150	26	96	13	16
PWA30	57	97	Anomic	83	160	147	25	77	9	16
PWA31	49	58	Brocas	58	163	98	19	74	162	12
PWA32	59	83	Anomic	78	190	132	25	91	26	19

PWA33	77	98	Anomic	98	206	183	29	86	93	16
PWA34	44	95	Anomic	95	196	151	27	96	12	12
PWA35	66	86	Anomic	73	--	--	--	--	123	16
PWA36	65	98	Anomic	95	187	163	22	81	24	19
PWA37	66	31	Broca's	0	101	40	3	39	41	18
PWA38	53	41	Wernicke's	7	144	74	17	64	25	12
PWA39	38	78	Anomic	55	173	139	22	77	53	16
PWA40	83	93	Anomic	95	172	145	22	79	39	16
PWA41	54	93	Anomic	80	193	143	27	96	115	16
PWA42	65	22	Conduction or Wernicke's	7	197	93	28	101	120	16
PWA43	66	70	Conduction	62	184	120	20	88	84	18
PWA44	53	48	Conduction or Wernicke's	7	178	93	24	92	107	16
PWA45	70	10	Global	0	13	30	3	17	76	12
PWA46	64	68	Anomic	13	146	102	14	71	18	18

PWA denotes patient with aphasia. BNT denotes the Boston Naming Test. The following headers denote standardized scores from the CLQT: attention (Attn), memory (Mem), executive function (Exec), visuospatial skills (VS). MPO denotes months post onset of stroke. Edu denotes years of education.

6.3. Strategy Analysis

Each participant's raw data on FB and PA category learning tasks (described in Chapter 2.3) were analyzed at the feature level, calculating the percentage of "B" responses made for each individual feature. Animals had ten features, each with a binary distribution (i.e. body pattern: *spots* or *stripes*), and we examined the percentage of "B" responses made for each binary option (percentage of "B" responses when the animal had the feature *spots*, percentage of "B" responses when the animal had the feature *stripes*). Recall that if feature was characteristic of prototypical animal B, it was reinforced as belonging to category B on 70% to 80% of trials. Correspondingly, the feature was reinforced as belonging to the opposite category on 30% to 20% of trails.

In the first step of our analyses, we calculated each individual's percentage of "B" responses for each binary dimension of the ten features. Next, we set up multiple model strategies adapted to our task and stimuli, based on those models presented by Gluck et al. (2002) and Meeter et al. (2006). Our first strategy, the optimal multi-cue strategy (OMC) was modeled as a strategy for which responses matched the actual "B" reinforcement rate for each dimension of each feature. In this model, for example, optimal categorization of the feature body pattern corresponded to a 70% "B" response rate for *spots* and a 30% B response rate for *stripes* (see Table 6.2). To produce results that truly fit the OMC strategy model, individuals had to produce near optimal categorization rates for multiple feature dimensions, not just one. Results with optimal categorization rates for all features suggest attention and effective learning of an entire pattern.

Next, we established twenty singleton cue strategies (SC), one for each feature dimension (A and B). Imagine that the feature body pattern was labeled as feature 1. The first singleton cue strategy (1A) was modeled as a strategy in which participants produced a "B" categorization rate of nearly 100% for all animals with a body pattern stripes and a nearly 0% "B" categorization rate for all animals with a body pattern *spots*. Model 1B would correspond to a near 0% "B" categorization rate for all animals with body pattern *stripes* and near 100% "B" categorization for all animals with body pattern *spots*. Based on the methods of Meeter et al (2006), in order to account for error, we set the model likelihood of responding "B" to *stripes* as variable π and its corresponding feature dimension (i.e. *spots*) as $1-\pi$; rather than setting these to 1 and 0, respectively. Meeter et al. (2006) evaluated error parameters, of .9, .95, .975 and .995. Researchers found that higher values of π produced best fits to data with few errors, while lower values of π produced ideal fits to data with many errors. This finding was logical since π represents an error tolerance criterion. A value of 0.95 was judged to optimize fits for a wide range of error rates. For our study therefore, we adopted a value of .95 for our parameter π. For each singleton cue strategy, responses to the remaining feature dimensions were modeled as chance, or a 50% "B" categorization rate (see Table 6.2).

Finally, we included a "random strategy" as proposed by Meeter et al. (2006). A random strategy is modeled as a 50% "B" response rate to each feature. As described by Meeter et al. (2006) behaviors that best fit random strategies can represent random behavior, or no strategy. Random strategies can also, however, encompass a multitude of strategies that simply deviate from those already modeled (OMC and SC in our study). Random strategies may therefore encompass no strategy, switching strategies, or a combination of probabilistic rules not captured by the other models. Including a random model into analyses helps reduce the number of falsely identified singleton cue and multi-cue strategy fits. Under stringent error criteria (π), such as 0.95, the range of responses fit by a random strategy is wide (see Figure 6.1). In the current study and subsequent analyses, we will call this range and strategy fit: random pattern (RP).

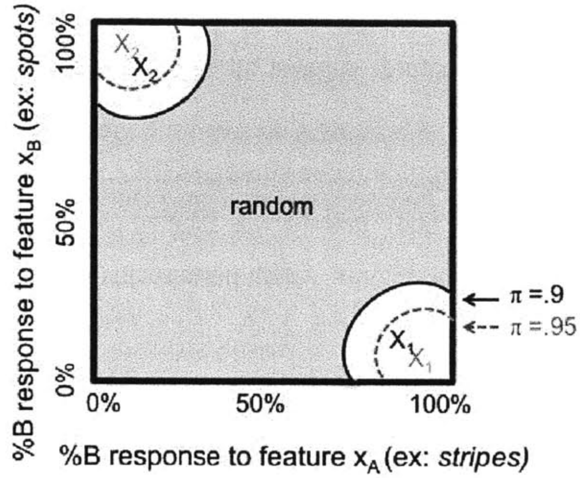

Figure 6.1: Response patterns modeled in the space of all %B values. This plot is modeled after Figure 2, of Meeter et al. (2006). This adaptation reflects two singleton cue strategies for a feature x. The upper left quadrant represents a near 100% B response categorization for all animals with dimension x_B (ex: spots) and near 0% B categorization of the opposite dimension x_A (ex: stripes). Semicircles represent the range of responses that would fit this singleton cue model under various parameters π. All areas shaded in gray that are not enclosed by semicircles represent patterns best fit by a "random strategy," in our study deemed a "random pattern" (RP). High parameters of π lead to a large range of responses best fit by RPs.

Finally, we adapted the quantitative methods proposed by Gluck et al., (2002) in order to quantify the fit of each participant's responses with each of our models. We used the following calculation to assign each participant with a fit score for each model:

$$\text{Score for Model } M = \frac{\sum_F (\#B\_expected_{F,M} - \#B\_actual_F)^2}{\sum_F (\#Bpresentations_F)^2}$$

using F to indicate feature (10 features, each with a binary value); $\#B\_expected_{F,M}$ for the number of times that a B feature would be expected to appear under model M; $\#B\_actual_F$ for the number of B responses made by the participant for that feature and $\#Bpresentations_F$ was the number of times that the feature B appeared in testing. In this manner we scored each participant's response fit with an OMC strategy, twenty SC strategies and a random pattern (RP). Each participant was assigned with a fit score between 0 and 1 for each strategy model. The score closest to 0 represented the closest model match.

Table 6.2
Set-up of model strategies

Feature		%B rate in training	OMC	RP	SC - 1A	SC - 1B	SC - 2A	SC - 2B	SC - 3A	SC - 3B	SC - 4A	SC - 4B	SC - 5A	SC - 5B	SC - 6A	SC - 6B	SC - 7A	SC - 7B	SC - 8A	SC - 8B	SC - 9A	SC - 9B	SC - 10A	SC - 10B
1	A	30%	0.3	0.5	**π**	**1-π**	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5
	B	70%	0.7	0.5	**1-π**	**π**	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5
2	A	20%	0.2	0.5	0.5	0.5	**π**	**1-π**	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5
	B	80%	0.8	0.5	0.5	0.5	**1-π**	**π**	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5
3	A	30%	0.3	0.5	0.5	0.5	0.5	0.5	**π**	**1-π**	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5
	B	70%	0.7	0.5	0.5	0.5	0.5	0.5	**1-π**	**π**	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5
4	A	20%	0.2	0.5	0.5	0.5	0.5	0.5	0.5	0.5	**π**	**1-π**	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5
	B	80%	0.8	0.5	0.5	0.5	0.5	0.5	0.5	0.5	**1-π**	**π**	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5
5	A	20%	0.2	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	**π**	**1-π**	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5
	B	80%	0.8	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	**1-π**	**π**	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5
6	A	20%	0.2	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	**π**	**1-π**	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5
	B	80%	0.8	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	**1-π**	**π**	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5
7	A	30%	0.3	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	**π**	**1-π**	0.5	0.5	0.5	0.5	0.5	0.5
	B	70%	0.7	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	**1-π**	**π**	0.5	0.5	0.5	0.5	0.5	0.5
8	A	20%	0.2	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	**π**	**1-π**	0.5	0.5	0.5	0.5
	B	80%	0.8	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	**1-π**	**π**	0.5	0.5	0.5	0.5
9	A	30%	0.3	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	**π**	**1-π**	0.5	0.5
	B	70%	0.7	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	**1-π**	**π**	0.5	0.5
10	A	30%	0.3	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	**π**	**1-π**
	B	70%	0.7	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	**1-π**	**π**

Parameter π was set to .95

OMC stands for optimal multi-cue strategy, in which responses were modeled to match that actual "B" reinforcement rate for each feature. SC stands for singleton strategy in which categorization rates approach 100% (π) for one feature value and approach 0% (1- π) for its alternative. RP stands for random pattern, modeled as a 50% "B" response rate to each feature.

6.4. Results

6.4.1. Strategy use following FB instruction

6.4.1.1. Controls. Strategy analyses over control participant data demonstrated that following FB instruction four control participants were best fit by an OMC strategy. Seven control participants were best fit by a SC strategy. Features were numbered from 1 to 10 and singleton users were found to attend to a variety of features, focusing on features 1, 4, 5, 6, 7, 8, 9 and 10; corresponding to body shape, nose, ears, head direction, body pattern, head direction and color. The variety of features focused on by singleton strategy users suggests that no single feature stood out as a more salient feature than the others. Only one control produced results that were fit by the RP.

Analyses of learning slope demonstrated that only two control participants produced scores that were suggestive of unsuccessful category learning under FB conditions (see Figure 6.2). Control participant 1 (CN1), the participant whose results fit the RP had a low slope of learning and results that were non-linear. This suggests a pattern of random responses that did not lead to effective category learning. We hypothesize that CN1 was unsuccessful at devising an effective strategy through training. The other control participant (Cn10) who did not learn following FB instruction was found to engage a SC strategy. SC strategies have been considered suboptimal, and in this case the participant focused on a feature that did not lead to successful overall categorization rates. All other control participants produced categorization scores that resulted in positive slopes of learning, which also satisfied conditions of linearity. Average slopes of learning for controls using an OMC strategy (n = 4) was 9.9, *SD* = 1.6. Average slopes of learning for controls using a SC strategy and demonstrating successful learning (n = 6) was 6.9, *SD* = 2.2. As seen in other studies, results demonstrate that category learning can be successfully achieved through OMC or SC strategies. Overall learning slopes were higher for participants engaging an OMC strategy than those engaging SC strategies.

6.4.1.2 Individuals with aphasia. Strategy analyses over patient participant data demonstrated that following FB instruction six patient participants were best fit by an OMC strategy. Nineteen individuals with aphasia were best fit by a SC strategy. Similar to what we observed in control participants, singleton users were found to attend to a variety of features. Patient participants focused on features 1, 2, 3, 5, 6, 8, 9 and 10; corresponding to tail shape, foot shape, headpiece, head direction, leg width, body pattern and color. The remaining 21 individuals with aphasia produced results that best fit a RP (see Figure 6.3).

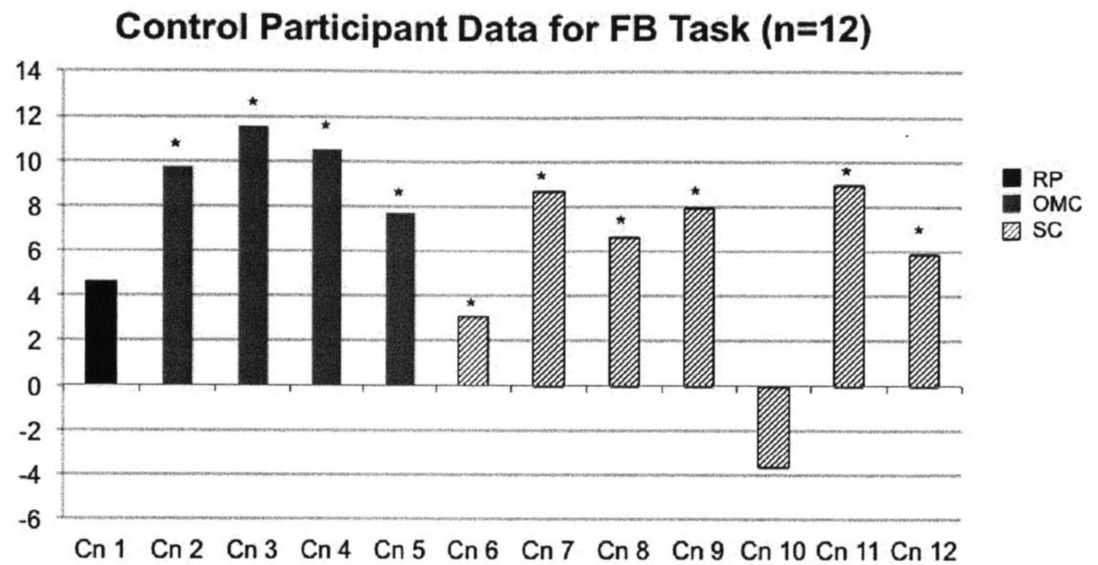

Figure 6.2: Control participant data for the FB task. The y-axis represents scores of learning. Recall that scores approaching positive ten represent ideal learning. Asterisks indicate scores that satisfied tests of linearity and approached positive ten. Marked scores represent successful category learning.

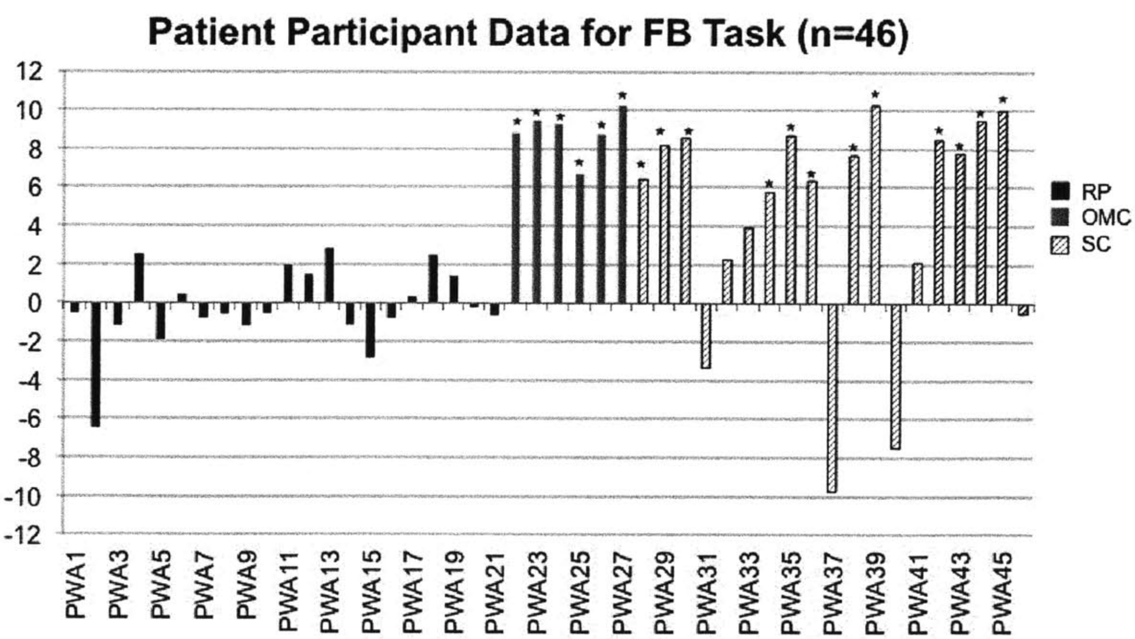

Figure 6.3: Patient participant data for the FB task. The y-axis represents scores of learning. Asterisks indicate scores that satisfied tests of linearity and approached positive ten, therefore representing successful category learning.

Analyses of learning slope demonstrated that none of the 21 individuals who engaged a RP during FB tasks successfully learned categories. As expected, all of the OMC strategy users had high scores of learning that satisfied conditions of linearity. Twelve of the SC strategy users were successful at category learning.

As this group was larger than the control group, we were able to conduct a one-way analysis of variance (ANOVA) using strategy as the between groups factor (OMC, RP and SC) to examine the group differences between FB learning slope and strategy use. The assumption of homogeneity of variance was not met for these data; therefore, the *Welch's F* test was used. Our one-way ANOVA yielded significant variation among strategy conditions; *Welch's* $F(2, 21.47) = 90.1$, $p = <.001$. A post-hoc Games Howell test demonstrated that slopes following RPs significantly differed from slopes following OMC strategies, $p < .001$ and SC strategies, $p < .01$. Slopes obtained under learning using a SC strategy also significantly differed from slopes obtained when classification engaged an OMC strategy, $p = .01$. Slope scores were highest when participants engaged an OMC strategy ($M = 8.9$, $SD = 1.2$) followed by scores obtained while engaging a SC strategy ($M = 4.5$, $SD = 5.9$) and finally a RP ($M = -.25$, $SD = 2.1$) (see Figure 6.4).

Thus, like controls, all individuals with aphasia who engaged OMC strategies during FB classification demonstrated successful learning of categories. The majority of patients engaging SC strategies also learned categories. In contrast, none of the participants with aphasia who engaged a RP following FB instruction were found to successfully learn categories. Engaging either an OMC strategy or SC strategy appears critical to successful learning under FB conditions. Engaging a RP following FB instruction is not ineffective.

6.4.1.3. FB instruction and cognitive-linguistic factors. In order to examine whether any differences arose in the cognitive-linguistic characteristics of OMC, SC and RP users following FB instruction, we conduced ANOVAs comparing aphasia quotient, BNT score, scores of attention, memory, executive function, and visuospatial skills as determined by the CLQT. We also included demographic variables of age, months post onset and education into analyses. All comparisons were found to be non-significant (see Figure 6.4). We observed a very mild trend in which RP users were found to have lower Raven's matrices scores, and lower scores of attention and executive function as determined by the CLQT.

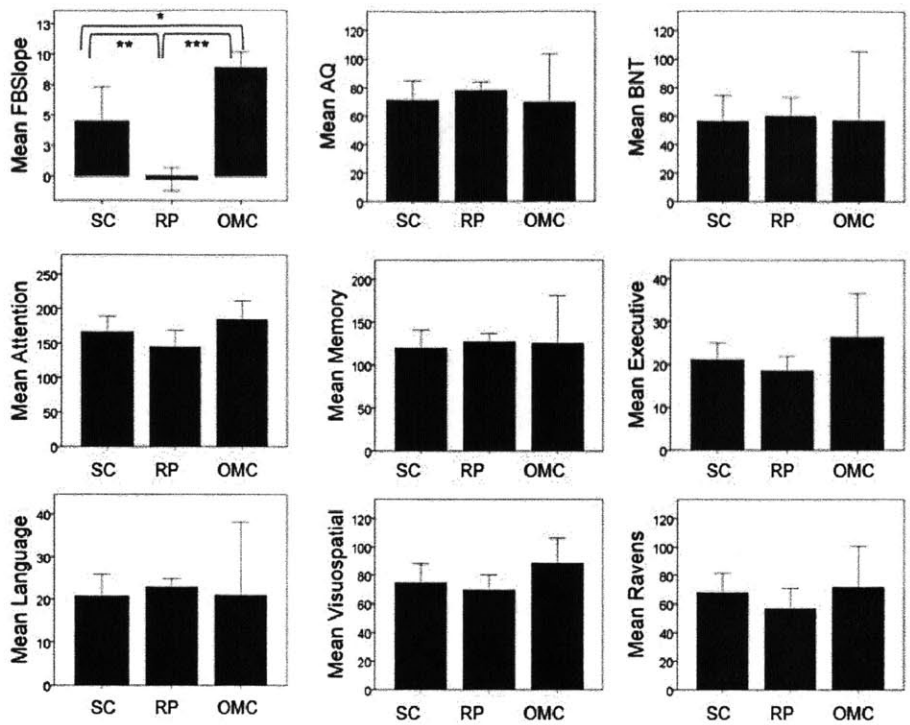

Figure 6.4: ANOVA results from analysis comparing strategy (OMC, RP, SC) with FB slope of learning and cognitive-linguistic measures. Analyses produced significant differences between FB slopes across all strategy conditions. No other comparisons were significant.

6.4.2. Strategy use following PA instruction

6.4.2.3. Controls. Following PA instruction, all twelve control participants were found to produce scores that best fit the RP. Interestingly, learning results using a RP following PA instruction are quite different from those observed in the FB condition. Following FB instruction, results that matched the RP led to unsuccessful learning and appeared to represent a failure to develop a strategy in training. In contrast, under PA instruction conditions, all control participants produced results that best fit the RP, and all controls also showed learning scores that approached positive ten and satisfied conditions of linearity (see Figure 6.5). Thus, across-the-board learning was observed under PA conditions for controls. The average group score of learning was 9.5, *SD* = 1.3.

Results suggest that under paired associate conditions, in which learning takes place through passive observation rather than through active feedback, developing a singleton cue or optimal cue strategy through the course of learning is not essential. Instead, in every case, successful learning for controls was achieved through responses that were classified as RPs.

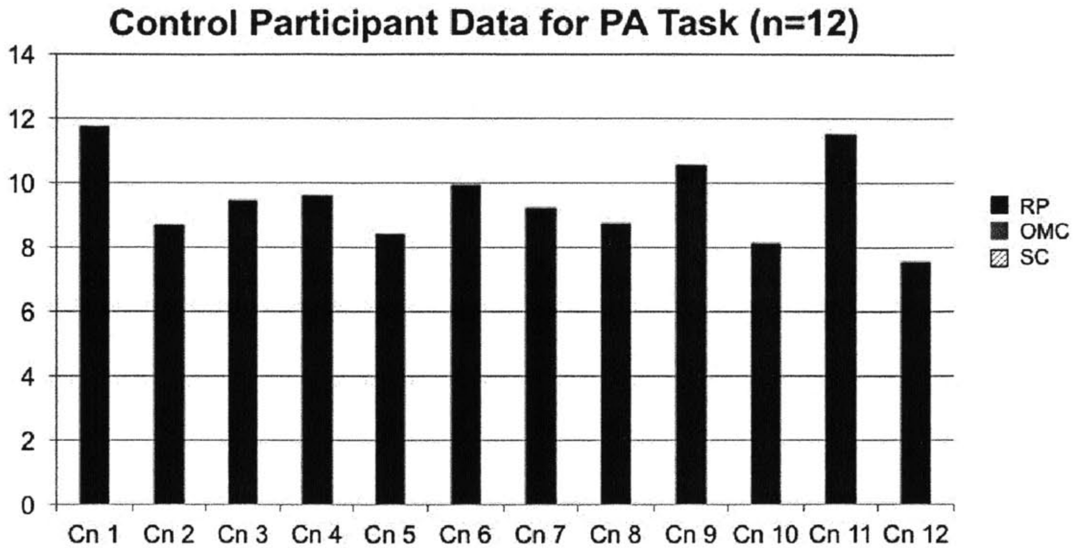

Figure 6.5: Control participant data for the PA task. Y-axis represents scores of learning, with a slope of positive ten representing ideal learning. All control participants were found to successfully learn categories following PA instruction conditions.

6.4.2.4. Individuals with aphasia. Similar to control results, strategy analyses on classification trials following PA instruction demonstrated that 43 of the 45 patient participants who completed the PA task engaged a RP. Patient slope scores following RP use encompassed a wide range ($M = 0.96$, $SD = 6.0$). Sixteen of these patients produced slope scores characterized as scores of successful learning. The remaining 27 produced slope scores that corresponded to unsuccessful learning (see Figure 6.6). Only two individuals with aphasia did not use a RP and instead engaged a SC strategy. Neither was successful at learning categories using this strategy under PA conditions.

6.4.2.5. PA instruction and cognitive-linguistic factors. We were again interested in examining how cognitive-linguistic factors and demographic variables impacted patient performance following PA instruction. For this condition, nearly all participants fell into the RP user group; however, unlike control participants who all learned successfully using a RP, a wide range of learning scores was seen under RP conditions in patients with aphasia. Therefore, we examined correlations between PA slope scores and cognitive-linguistic variables for RP users (n = 43). Analyses yielded one significant correlation between PA slope of learning and visuospatial skills as determined by the CLQT; r (43) = .35, p = .02. All other correlations were non-significant. Similarly, a one-way ANOVA examining the cognitive-linguistic characteristics of learners and non-learners who implemented SC strategies revealed no significant differences.

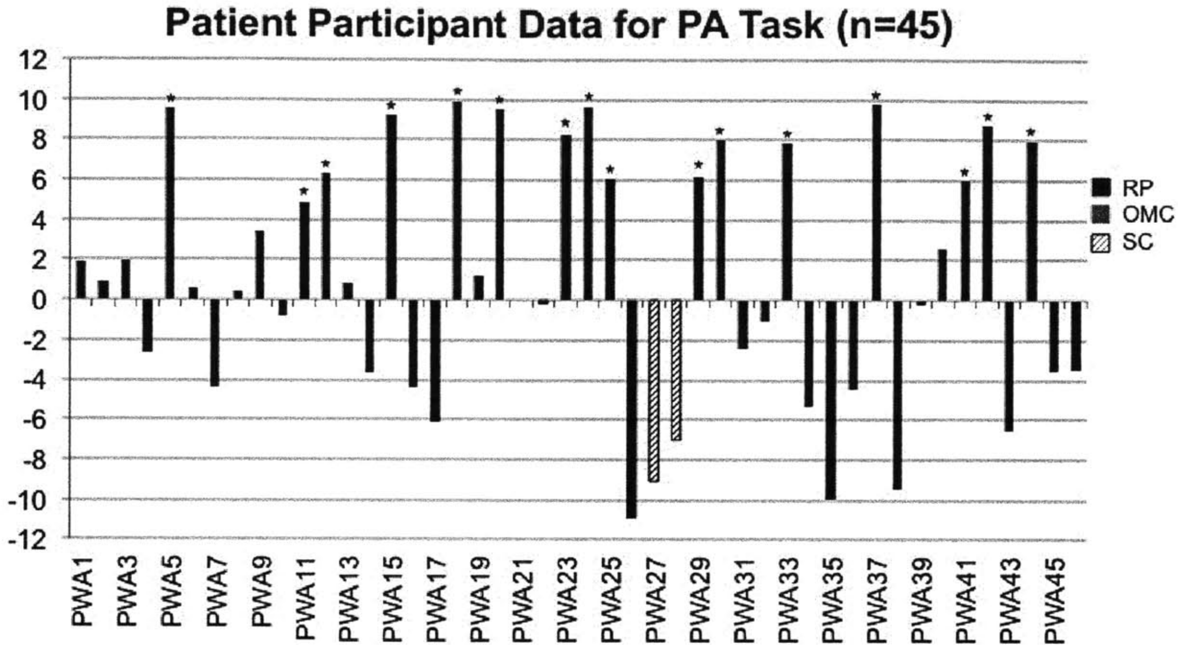

Figure 6.6: Patient participant data for the PA task. Forty-three of forty-five participants engaged a RP. The y-axis represents scores of learning. Asterisks indicate scores that satisfied tests of linearity and approached positive ten, therefore representing successful category learning.

6.4.3. Summary of results. Control participants and individuals with aphasia showed a similar overall pattern in which they engaged a variety of strategies following FB training. Under FB conditions, the use of OMC strategies and of SC strategies led to effective categorization in testing phases following training. Data that were best fit by a RP under FB conditions resulted in poor learning in all cases. Results suggest that in FB conditions, where individuals receive feedback on a trial-by-trial basis, development of an OMC or SC strategy is critical for successful learning.

Following PA training, a different pattern of strategy use arose. All controls and nearly all individuals with aphasia produced results that best fit a RP. All control participants showed successful learning following PA instruction. Sixteen of 45 individuals with aphasia showed successful learning following PA instruction.

6.5. Discussion

In this study, we aimed to explore strategy use in patients with aphasia compared to control participants during two different versions of a probabilistic category learning task: FB and PA. Differences arose in strategy use both between groups (controls and patients with aphasia) and between conditions (FB and PA). All control participants showed successful category learning following PA instruction. Ten of these controls also showed successful learning following FB instruction. For our individuals with aphasia, 18 learned following FB instruction compared with 16 following PA instruction.

We observed that following FB instruction, participants were able to produce scores of successful learning using both OMC strategies and SC strategies. Successful learning following OMC strategies is not surprising as this reflects that through the course of training, participants learned to produce responses that closely matched the actual reinforcement rate of multiple animal features. As noted in the introduction, similar patterns have been observed in previous studies examining healthy populations (Gluck et al., 2002; Hopkins et al., 2004; Knowlton et al., 1994; Meeter et al., 2006; Shohamy et al., 2008; Shohamy, Myers, Onlaor, et al., 2004) Though our participants only underwent 60 training trails with feedback, four control participants and six patient participants were able to implement a complex OMC strategy.

Based on prior studies that found that patients with amnesia and patients with PD were not able to implement complex strategies (Hopkins et al., 2004; Meeter et al., 2008; Shohamy, Myers, Onlaor, et al., 2004), we had hypothesized that individuals with aphasia might also rely on simple strategies. In our study however, six individuals with aphasia produced results that best fit a complex OMC strategy following FB instruction. Findings suggest that a small group of individuals with aphasia have preserved abilities to rapidly develop complex, multi-dimensional strategies. Feedback-based probablistic learning tasks are thought to rely heavily on basal ganglia circuits, regions specifically damaged in PD (Meeter et al., 2008 for review). For the case of aphasia, lesions are heterogeneous and unilateral, not always affecting these structures. It is therefore likely that many individuals with aphasia have neural networks capable of supporting the development of complex strategies to engage in learning of this sort. Cognitive-linguistic factors were not sufficient to predict which individuals with aphasia had these complex probabilistic learning abilities.

SC strategy use led to successful learning for the majority of control participants and for twelve of the nineteen individuals with aphasia that implemented a SC strategy. Individuals focused on a variety of features in SC strategy use suggesting that no one feature was more salient than others. Successful patterns of learning using SC strategies are consistent with previous results in healthy individuals and in clinical populations (Gluck et al., 2002; Rustemeier et al., 2013; Shohamy, Myers, Grossman et al., 2004; Shohamy, Myers, Onlaor et al., 2004). These individuals likely identified a feature with a high reinforcement rate in training and implemented this strategy in testing phases. Based on previous research that showed a gradual progression from singleton cue to multi-cue strategies in learning, one might predict that these individuals would have progressed to an OMC strategy given additional training trials.

Interestingly, seven individuals with aphasia focused on one feature during testing, however produced poor overall scores of learning. This group did not significantly differ from the learner group on standardized cognitive-linguistic measures. Results suggest an alternate profile, in which individuals focused in on a single-feature, but were not effective at selecting a feature with an ideal reinforcement rate. Such a pattern may suggest that individuals were unable to attend to multiple features at once and therefore honed in on a single feature regardless of its reinforcement rate in training. Participants may otherwise have realized that certain features had high reinforcement rates with a particular category, but experienced difficulty recalling the correct category membership of that particular feature.

In contrast to OMC and SC strategy implementation, results that best fit a RP following FB instruction produced poor overall category learning in all cases. For these individuals (1 control participant, 21 individuals with aphasia), training did not lead to an optimization of responses or to a focus on a single feature with a high reinforcement rate. Instead, we propose that these individuals were unable to develop strategies in training, or had difficulty tracking feedback and refining strategies. Such deficits were posited in Meeter et al.'s (2006) study involving patients with amnesia. Researchers proposed that deficits in recall of attempted strategies and resulting feedback likely accounted for the observed lack of strategy implementation. Shohamy, Myers, Onlaor et al. (2004) hypothesized that deficits of integration, working memory deficits or impairments in switching between strategies led to poor strategy-development in PD patients. Any of these factors could have contributed to the random response rates produced by our RP group; all of which resulted in poor scores of learning.

Critically, results suggest that in order to successfully learn categories following FB instruction, one must implement an OMC or an SC strategy. In the FB condition of our task, participants were presented with a stimulus item and were instructed to guess to which category it belonged. Only following a response were participants provided with feedback telling them whether they were correct or incorrect. Under such a paradigm, participants are expected to accumulate information about the probabilistic environment through the course of multiple trials (Knowlton et al., 1994). Current results suggest that under this instruction paradigm, participants had to adapt and use feedback in order to succeed with learning. The feedback aspect of the task required strategy development.

Meeter et al. (2008) reviewed multiple mechanisms that have been hypothesized to be engaged during feedback-based probabilistic category learning. Three major mechanisms were outlined: rule-based learning, information-integration and exemplar memorization. The predominant reliance on SC strategies under FB conditions in our experiment implies that participants devised rules or engaged in active hypothesis testing through learning; mechanisms that likely engage explicit processes (Ashby et al., 1998; Ashby & Maddox, 2011). OMC strategies may reflect information-integration, the process of gradually integrating information across multiple dimensions through the course of learning (Ashby & Ell, 2001). Such processes are hypothesized to rely on reward-mediated procedural networks (Ashby & Maddox, 2011; Ashby et al., 2002). Processes of hypothesis testing, tracking or monitoring appear to be critical to learning during our FB task, whether they were conscious or unconscious.

In contrast, our strategy analyses following PA instruction produced compelling results, in which fifty-five of the fifty-seven individuals who completed the task produced scores that best fit a RP. Considered alongside FB results, one would anticipate that all participants therefore produced poor scores of learning. However, despite a best fit to RPs, all control participants showed scores of successful learning following PA training. Sixteen individuals with aphasia were also successful in testing phases. These results are consistent with results observed by Shohamy, Myers, Grossman et al. (2004). Of their 20 participants (9 controls and 11 individuals with PD), only three produced results that fit multi-cue, single cue or singleton cue strategies following observational conditions of probabilistic learning. Results from the remaining participants were not consistent with any of the models. Importantly, even though results were not consistent with modeled strategies, successful learning was observed. We, therefore, suggest that distinct mechanisms not captured through OMC and SC models are at play during PA learning.

Much research has already demonstrated that distinct systems are engaged during FB versus PA learning (Ashby et al., 2002; Poldrack et al., 2001) and the differences in strategy use seen in FB and PA conditions of our task support this hypothesis. We further propose that the mechanisms behind RP use following FB instruction are different from those following PA instruction that leads to successful learning. As described above, hypothesis testing, tracking and monitoring appear to be inherent to FB learning. Importantly, these do not appear to play a critical role following PA instruction.

We propose that during PA learning, participants are undergoing prototype extraction in which they implicitly learn the regularities among stimuli that determine category membership. During passive observation of category items, participants build an abstract representation of prototypes based on the statistical properties of items seen in training, thus forming a broader understanding of the overall category. Many studies propose that passive exposure to stimulus items within a category leads to this type of extraction of common features and promotes recognition of novel items (Kéri, 2003; Knowlton & Squire, 1993; Reed, Squire, Patalano, Smith, & Jonides, 1999; Smith, 2008; Squire & Knowlton, 1995). Such prototype extraction learning has been proposed to rely on implicit processes and is described as being systematically different from intentional learning (Smith, 2008; Smith & Grossman, 2008). Feedback has actually been described as disrupting this type of process as the intention to learn engages explicit processes (Smith, 2008).

We therefore propose that during PA learning of our task, participants engaged in implicit tracking of similarities and statistical properties of category exemplars throughout PA instruction. In support of this interpretation, prototype learning has been hypothesized to rely on perceptual learning with a high dependence on the visual cortex (Ashby & Ell, 2001; Seger & Miller, 2010). This may explain the significant correlation observed between PA scores of learning and visuospatial skills as measured by the CLQT.

Compelling differences were observed following FB and PA instruction methods. Notably, RP use was found to be detrimental to learning under FB conditions. In contrast, nearly all participants engaged RPs during PA learning and often experienced successful category learning. Findings provide support for the hypothesis that these methods of instruction engage distinct processes. Results also demonstrate that subtle alterations in instruction can lead to the distinct engagement of strategies, some of which may be more or less beneficial for individual patients. While it is important to consider tasks and targets in therapy, current results reiterate that the way in which therapy is administered is potentially of equal importance.

7. Conclusion

This thesis has presented a collection of studies exploring the nonlinguistic learning ability of individuals with aphasia. Our work was motivated in large part by the fact that predicting outcomes continues to be a problem facing clinicians in aphasia. Clinicians frequently encounter patients with similar deficits and linguistic profiles who show variable patterns of progress following structured therapy programs. Such observations led to the hypothesis that important factors are missing in our current diagnostic characterization of individuals with aphasia and our understanding of the mechanisms of therapy. As described in the introduction, we propose that learning, which is intrinsically linked to rehabilitation in aphasia, presents an avenue through which individual variability following treatments might be better understood and explained.

In our first experiment, data collected from 19 patients with aphasia and 12 healthy age-matched controls established a proof of principle that patients with aphasia do not learn non-linguistic information in the same manner as controls. Nearly all age-matched controls successfully learned categories following both methods of instruction, however only 11 out of 19 patients showed successful learning following at least one method of instruction. Of these 11 learners, 8 patients demonstrated a preference for learning following FB or PA instruction. The remaining three patients learned successfully following both methods of instruction. Nonverbal learning scores did not correlate with language ability, further suggesting that general learning ability is not predicted by language ability.

Interestingly, a cluster analysis produced three meaningful clusters related to AQ scores as determined by the WAB. Two clusters, one including patients with the lowest AQ scores (greatest degree of aphasia severity) and another including patients with the highest AQ scores (lowest degree of severity) demonstrated successful learning of our tasks. In other words, learners came from the two extremes with respect to severity of aphasia, while, with the exception of one patient, all non-learners had AQ scores that fell in the middle range of scores on standardized tests (see Figure 3.8). Findings support the hypothesis that brain damage to areas that are not themselves considered critical to learning can, in many cases, lead to impairments in nonlinguistic category learning. Importantly, nonverbal learning scores did not correlate with language ability, further suggesting that learning ability is not predicted by language ability. As a result of this experiment, we also devised a metric to quantify success on our category learning tasks. This metric allowed us to examine patterns and behaviors related to learning in subsequent experiments.

In our second experiment, motivated by language therapy studies that have examined the impact of complexity on patterns of generalization following treatment, as well as by research demonstrating the variable impacts of training method and stimulus characteristics on learning; we investigated learning following typical (simple) and atypical (complex) training conditions. Typical training conditions are thought to facilitate learning through an emphasis on salient category features. Atypical training conditions are thought to promote generalization to untrained within-category items through exposure to within-category feature variability. Atypical training conditions are considered more complex than typical training conditions, as successful learning requires that participants extract central category tendencies from training items that contain variability.

Our experiment demonstrated, as hypothesized, that controls and individuals with aphasia were able to successfully learn under typical training conditions. This condition was found to facilitate learning even for individuals with aphasia who were unable to learn categories under baseline conditions established in experiment 1. Most controls were also able to maintain learning under complex, atypical training conditions. A smaller group of individuals with aphasia were able to learn under these more complex conditions. We did note that those patients who learned atypical conditions generally succeeded at baseline tasks included in experiment 1. Though task requirements were different, results present a preliminary measure of test-retest reliability. Once again, standardized cognitive-linguistic measures were not predictive of which individuals with aphasia were robust, atypical learners versus those who learned only from facilitative conditions.

Results suggest that variability arises within the learning ability of individuals with aphasia and led us to hypothesize how these relate to treatment. Aphasia treatment studies have suggested that treatment focused on complex tasks and targets are superior for promoting generalization than treatment focused on simple targets. Considering this, patients with aphasia who demonstrated robust abilities to extract commonalities from complex training items during nonlinguistic learning might also be those for whom complex therapy paradigms will promote generalization. In contrast, many patients with aphasia were unable to perform such extraction during nonlinguistic learning and therefore might not be candidates as appropriate for complex therapies.

In experiment 3, we aimed to bridge the gap between abstract category learning tasks and actual therapy, as the goal of our research is to apply findings to a therapy setting. In this experiment, we enrolled individuals with aphasia in a theoretically motivated sentence comprehension treatment, assigning each a metric of learning ability. Results demonstrated that FB learning ability score was the only measure that significantly correlated with effect sizes following treatment. The best model predicting treatment outcomes combined measures of FB learning with years of education. We proposed that our sentence comprehension treatment likely recruited many of the skills of integration of visual information, strategy selection and response selection important for FB learning.

Interestingly, through this study, we noticed that a subgroup of participants attended to only one feature following FB instruction, but not PA instruction. This observation led to the development of experiment 4 in which we completed a systematic investigation into strategy use following FB and PA instruction. Experiment 4 revealed that distinct patterns of strategy use arose following FB and PA instruction. The implementation of OMC or SC strategies was found to be critical to successful FB learning. In contrast, all controls and 43 patients with aphasia implemented a RP during PA learning. Implementing this strategy led to successful learning for all controls and for 16 individuals with aphasia. Results suggest that distinct mechanisms are at play during PA learning that are not captured by OMC and SC strategies. Results bring attention to the fact that characteristics of instruction significantly impact the ways in which individuals approach a task. Cognitive neuroscientists have understood for many years the significance that such an implication has on observed behavioral patterns and learning. The current work, however, represents the first time that the importance of method of instruction is brought to light in aphasia research. The finding is simple, yet fundamental. The means with which input is provided to patients likely influences the way that they engage with that input, also impacting the underlying mechanisms that are recruited.

The sum of these studies has established a preliminary understanding of nonlinguistic category learning in aphasia. Experiments have probed the impact of input variables on learning. We also explored how an abstract metric of learning ability might relate to therapy outcomes, finding a positive relationship between FB learning scores and success with therapy. Finally, we examined the participant-driven factor of strategy selection determining that individuals approach learning tasks in a variety of ways, and furthermore; that method of instruction has a significant impact on strategy implementation.

These represent an important body of findings, as they are the first systematic exploration into nonlinguistic learning in stroke-related aphasia. Prior therapy studies have focused on language deficits in order to identify appropriate tasks and targets for therapy. Additional studies have explored processes of new word learning in patients with aphasia. As aphasia is a deficit defined by impairments in language however, a perspective not so heavily laden with language is important to incorporate into our understanding of the disorder. In addition, our findings and approach can be extended to other populations characterized by language disorders such as semantic dementia, frontotemporal dementia and primary progressive aphasia.

Our project has presented an innovative approach, using nonlinguistic paradigms that are well established in cognitive neuroscience, but that to date have not been examined to understand the mechanisms of learning in patients with language impairment. As described in the introduction, much research now recognizes that regions critical for language are part of an extensive, interconnected network within the brain. Conventional aphasia research has for the most part narrowly focused on regions critical to language; neglecting to explore the broader impact that brain damage produced by aphasia-inducing strokes might have on nonlinguistic networks. We aimed to introduce a fundamentally new approach that looked 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. In our work, we proposed the novel hypothesis that cognitive-linguistic deficits may be accompanied by deficits in the general architecture supporting learning. Our results have supported this hypothesis.

In addition, throughout our experiments behaviors that surfaced during learning were not correlated with measures of language severity or other standardized metrics. We thus suggest for the first time that differential deficits in language and learning networks are present in aphasia.

Applied to a clinical setting, we propose that those patients who appear to have higher-level language skills do not necessarily present with the most intact cognitive or pattern abstraction systems. Instead, these skills are likely affected to different degrees within individuals with aphasia, contributing to our current inefficiency at predicting outcomes. Patients with deficits that extend beyond language may require additional reinforcement or training in therapy in order to facilitate the efficient integration and absorption of information.

Our strategy work suggests that control participants are able to independently select effective strategies regardless of the method of instruction. Cognitive neuroscience research has demonstrated that healthy individuals are equipped with multiple neural systems that support learning. Presented with stimulus and task demands, healthy individuals appear adept at selecting and engaging effective supporting mechanisms for learning. In our patients with aphasia, a subgroup of individuals was not able to implement strategies that promoted effective learning. Results might suggest that patients with aphasia are more limited in the number of strategies available to them or in their ability to rapidly adapt to task demands. Patients may therefore require additional instruction to help them optimally engage strategies and thus neural systems during learning.

Much still remains to be understood about learning in aphasia and its contribution to therapy and therapy outcomes. A logical next progression would be to incorporate neuroimaging methodologies to identify how neural substrates relate to observed patterns of behavior. In addition, neuroimaging will provide additional insights into the relationship between behavioral measures, aphasia presentation and site and extent of lesion.

We have proposed many hypotheses of the potential relationship between patterns of nonverbal learning and therapy that remain to be tested. We have speculated, for example, that our findings about stimulus complexity in nonverbal learning might inform appropriate stimulus selection for individuals with aphasia. If this is the case, we will finally have taken a much needed step towards individualized treatment in aphasia.

Overall, we propose that the nonverbal domain of learning presents a window into the relearning or reaccesing of language that is brought about through rehabilitation. In the future, we hope that assessments can include a metric of learning that helps identify strategies and supporting cognitive capabilities that are selectively intact in patients. A better understanding of these supporting systems may be the gateway to developing effective, individually tailored treatment for patients with aphasia.

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