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Nonlinguistic Learning in Individuals With Aphasia: Effects of Training Method and Stimulus Characteristics

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Purpose: The purpose of the current study was to explore nonlinguistic learning ability in individuals with aphasia, examining the impact of stimulus typicality and feedback on success with learning.
Method: Eighteen individuals with aphasia and 8 nonaphasic controls participated in this study. All participants completed 4 computerized, nonlinguistic category-learning tasks. Learning ability was probed under 2 methods of instruction: feedback-based (FB) and paired-associate (PA). The impact of task complexity on learning ability was also examined, comparing 2 stimulus conditions: typical and atypical. Performance was compared between groups and across conditions.
Results: The controls were able to successfully learn categories under all conditions. For the individuals with aphasia, 2 patterns of performance arose: One subgroup of individuals was able to maintain learning across task manipulations and conditions; the other subgroup demonstrated a sensitivity to task complexity, learning successfully only in the typical training conditions.
Conclusion: Results support the hypothesis that impairments of general learning are present in individuals with aphasia. Some individuals demonstrated the ability to extract category information under complex training conditions; others learned only under conditions that were simplified and that emphasized salient category features. Overall, the typical training condition facilitated learning for all of the participants. Findings have implications for treatment, which are discussed.

Key Words: adults, aphasia, language, category learning

Although aphasia is a deficit that is characterized primarily by impairments in language, an increasing body of research has recently been dedicated to understanding the contribution of cognitive deficits of attention, concept knowledge, executive function, and memory on language construction, use, and rehabilitation in people with aphasia (PWA; Erickson, Goldinger, & LaPointe, 1996; Fridriksson, Nettles, Davis, Morrow, & Montgomery, 2006; Helm-Estabrooks, 2002; Hula & McNeil, 2008; Keil & Kaszniak, 2002; Lesniak, Bak, Czepiel, Seniow, & Czlonkowska, 2008; Murray, 2012; Peach, Rubin, & Newhoff, 1994; Ramsberger, 2005; Zinn, Bosworth, Hoenig, & Swartwelder, 2007). Expanding on these investigations into cognitive deficits that likely impact rehabilitation outcomes, we focused on learning ability, a skill that, to date, has received limited attention in the field of aphasia.

Researchers have identified learning ability as a central factor in rehabilitation (Ferguson, 1999; Hopper & Holland, 2005) whether improvement involves facilitating access to previously mastered information, developing compensatory strategies in light of deficits, or learning new information (Kelly & Armstrong, 2009; Tuomiranta et al., 2011). In spite of this, only a select number of studies have been dedicated to understanding how PWA learn. Studies have shown that PWA are capable of demonstrating new verbal learning (Breitenstein, Kamping, Jansen, Schomacher, & Knecht, 2004; Freedman & Martin, 2001; Gupta, Martin, Abbs, Schwartz, & Lipinski, 2006; Kelly & Armstrong, 2009; Marshall, Neuburger, & Phillips, 1992; Tuomiranta et al., 2011), and in addition, that learning ability appears to be related to PWA's profiles of linguistic (Grossman & Carey, 1987; Gupta et al., 2006) and cognitive strengths and deficits (Freedman & Martin, 2001). Our understanding of learning in PWA is still limited, however, particularly because all of the recent studies have explored verbal learning without exploring nonverbal learning. Language is the primary deficit in aphasia, so it is likely that language deficits interfere with patterns of learning when tasks are verbal or grammatically structured. We hypothesize that behavioral patterns observed during nonverbal

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learning tasks will shed new light on the process of learning in PWA.

As a first step toward examining this possibility, we recently explored nonlinguistic category learning in PWA and age-matched controls (Vallila-Rohter & Kiran, 2013). In this study, 19 PWA and 12 nonaphasic controls were tested as they completed computerized nonlinguistic, multidimensional category-learning tasks. Tasks were similar to those described in the current paper. Results showed that different profiles of learning arose between the PWA and the controls. Only 11 out of the 19 PWA showed learning of categories compared with across-the-board learning by the control participants. Interestingly, measures of participants' cognitive or linguistic abilities did not correlate with their performance on learning tasks. These results highlight that nonlinguistic learning ability is affected in PWA. The reasons for incomplete learning in this group, however, remain unanswered and merit further investigation.

Although little is known about nonverbal learning in PWA, studies involving other clinical populations and 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 individuals with brain damage. Individuals 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 (Ell, Weinstein, & Ivry, 2010; Filoteo & Maddox, 2007; Filoteo, Maddox, Ing, Zizak, & Song, 2005; Price, 2006). These individuals show intact artificial grammar learning (Reber & Squire, 1999; Smith, Siegert, & McDowall, 2001; Witt, Nuhsman, & Deuschl, 2002) and intact information integration learning under conditions of limited complexity (Ashby et al., 2003; Filoteo, Maddox, Salmon, & Song, 2005). Similarly, individuals with amnesia are sensitive to instruction method, demonstrating impairments in learning that involves recall and recognition (Filoteo, Maddox, & Davis, 2001; Graf, Squire, & Mandler; 1984; Knowlton, Ramus, & Squire, 1992), yet showing successful learning of probabilistic classification tasks (Knowlton et al., 1994).

The mechanism underlying the facilitation or impairment of learning for these individuals is thought to be related to the existence of multiple memory systems that rely on different neurobiological structures and support learning in different ways. Many types of learning rely on the recall of individual instances, facts, or events consciously or unconsciously in order to form associations between previously unrelated stimuli. Conscious learning of this type, termed explicit learning, is thought to rely heavily on the hippocampus and medial temporal lobe structures (Seger & Miller, 2010; Squire, 1992, for review). Explicit systems are considered important for rule learning (Breitenstein et al., 2005; Squire, 1992; Warringon & Weiskrantz, 1982; Winocur & Weiskrantz, 1976), and, as described in the competition between verbal and implicit systems model (Ashby, Alfonso-Reese, Turken, & Waldron, 1998; Maddox & Ashby, 2004, for review), explicit systems are likely engaged in the early stages of many additional types of category learning. In these stages, learners are thought to engage logic and reasoning to form hypotheses; often verbalizable ones. Hypotheses are then tested and results are monitored. Such processes are 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 et al., 1998; Keri, 2003; Knowlton, Mangels, & Squire, 1996; Knowlton & Squire, 1993; Maddox & Ashby, 2004; Seger & Miller, 2010, for review). This type of 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, which gradually strengthens the association between cues and responses (Seger & Miller, 2010; Shohamy et al., 2004; Shohamy, Myers, Kalanithi & Gluck, 2008). Therefore, feedback appears to be critical to this type of learning (Ashby et al., 1998; Ashby & Crossley, 2010; Ashby & Maddox, 2011; Ashby & Valentin, 2005; Keri, 2003; Maddox & Ashby, 2004; Maddox, Ashby, Ing, & Pichening, 2004; Seger & Miller, 2010).

Although certain conditions are thought to emphasize the engagement of one memory system over another, research has suggested that these systems can interact or compete throughout learning (Ashby et al., 2008; Ashby & Crossley, 2012; Ashby & Valentin, 2005; Cincotta & Seger, 2007; Moody, Bookheimer, Vanek, & Knowlton, 2004; Poldrack et al., 2001; Seger & Miller, 2010). Of particular relevance to the current study, Ashby et al. (2002) explored learning strategies employed under conditions of feedback-based (FB) and paired-associate (PA; observational) training on an information integration task. Results suggested that the presence of feedback led to an effective reliance on automatic processes of information integration. In contrast, observational paradigms led to a high reliance on rule-based strategies. Ashby et al. (2002) proposed that observation learning reduced instances of unexpected reward and therefore interfered with the automatic processes of information integration. In our study, we examined the rates of successful learning when participants learned multidimensional categories under conditions with and without feedback.

Another factor that we explored in the current study is stimulus complexity, as complexity has been the focus of considerable research in aphasia rehabilitation. Studies in aphasia have noted generalization from complex to less complex related structures. This has been observed following both syntactic therapy (Thompson, 2001; Thomson, Ballard, & Shapiro, 1998; Thompson et al., 1997; Thompson, Shapiro, & Roberts, 1993) and semantic therapy (Kiran, 2007, 2008; Kiran, Sandberg, & Sebastian, 2011; Kiran & Thompson, 2003a, 2003b). Such observations led to the formulation of the complexity account of treatment efficacy (CATE) hypothesis (Thompson, Shapiro, Kiran, & Sobecks, 2003), which draws attention to the potential impact of stimulus complexity on treatment outcomes and generalization patterns in PWA.

Motivation for the development of CATE came from results that were 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 computational experiment focused on the impact of training typical or atypical words produced two major findings: First, the retraining simulation showed better overall learning 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 highlights 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, resulting in limited generalization.

In the current study, we aimed to better understand nonlinguistic category-learning ability in PWA, exploring the impacts of both instruction method and stimulus characteristics on an individual's success with learning. We examined nonlinguistic learning ability in PWA and nonaphasic controls, comparing FB instruction and PA instruction. Within these two conditions, we explored the impact of stimulus characteristics, comparing one condition in which training emphasized salient category features (*typical training*) and another condition in which training highlighted feature variability within categories (*atypical training*). We further explored whether demographic variables or standardized measures of cognitive–linguistic ability demonstrated a predictive relationship with participants' learning scores.

We hypothesized that participants would learn better under FB conditions, as research has suggested that implicit systems that are sensitive to feedback are better suited for complex category learning that requires information integration (Ashby et al., 2002). We also hypothesized that typical training would result in better overall learning rates than atypical training. Based on connectionist theories, we proposed that following atypical training, participants would show generalization of learning to typical items.

Method

Participants

Eighteen (10 men and eight women) PWA subsequent to single left-hemisphere stroke participated in this study. The mean age of participants was 61.32 (ranging from 33.7 to 77.2 years; *SD* = 12.17), and they had completed an average of 15.83 years of education (ranging from 11 to 19 years; *SD* = 2.92; see Table 1). Fifteen PWA were Caucasian, two were Black, and one was of Hispanic ethnicity. The PWA were tested at least 6 months after the onset of their stroke and had degrees of aphasia severity ranging from mild to severe, as determined by Western Aphasia Battery (WAB; Kertesz, 1982) aphasia quotients (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, as determined by the WAB. All of the PWA were premorbidly right-handed and were medically and neurologically stable at the time of testing. One participant dropped out of the study before completing the diagnostic test battery and therefore is missing measures of cognitive–linguistic ability and was not assigned an aphasia type.

Eight nonaphasic controls (three men and five women) were also recruited to participate in this study. These participants had no known history of neurological disease; psychiatric disorder; or developmental speech, language or learning abilities. The mean age of the controls was 62.87 (ranging from 57.2 to 72.6 years; *SD* = 6.58), and they had completed an average of 16.5 years of education (ranging from 16 to 18 years; *SD* = 1.03; see Table 1). One control, Cn 4, was left-handed. All of the controls were Caucasian. Because we were most interested in patient patterns of learning, we included only a small group of similarly aged nonaphasic controls to serve as a baseline.

Stimuli

Stimuli for the current study were two sets of cartoon animals that were created by Zeithamova, Maddox, and Schnyer (2008) and were first reported in Vallila-Rohter and Kiran (2013). Each animal had one of two possible feature values for 10 dimensions: neck length (long or short), tail shape (straight or curled), toes (pointed or curved), snout (round or pointed), ears (pointed or rounded), color (purple or pink), body shape (pyramidal or round), body pattern (spots or stripes), head direction (upward or downward), and leg length (long or short). Two orthogonal categories were created per stimulus set. For each category, one animal was selected as prototype A, with the animal that differed from that prototype by all 10 dimensions identified as prototype B. The remaining 1,024 animals in each stimulus set were grouped by their *distance* from prototype A, each distance increment describing the number of features by which the animals differed from prototype A. Thus, animals at distance 1 from prototype A had a nine-feature overlap with that prototype, animals at distance 2 had an eight-feature overlap with prototype A, and so forth. The binary nature of the features meant that with each increasing distance increment from prototype A, the animals had an increasing feature overlap with the prototypical animal of the opposite category, B (i.e., animals at distance 1 had a nine-feature overlap with prototype A and a one-feature overlap with prototype B, animals at distance 2 had an eight-feature overlap with prototype A and a two-feature overlap with prototype B, etc.). In this manner, two categories were established along a continuum that depended on feature overlap with each prototypical animal.

Table 1. Study participants' demographics.

ID	Age	Gender	Ed.	MPO	Aphasia type[a]	Comp.[b]	Attn.[c]	Mem.[c]	Exec.[c]	Visuo[c]	BNT	AQ
IWA1	33.7	Female	14	6	Con.	91	WNL	Sev	Mod	WNL	0	24.8
IWA 2	49.7	Female	18	24	Anomic	185	WNL	WNL	WNL	WNL	100.0	93.9
IWA 3	52.7	Female	12	25	Wern.	116	WNL	Sev	Mod	WNL	6.7	41.4
IWA 4	52.7	Male	16	107	Con./Wern.	142	Mild	Sev	WNL	WNL	6.7	48.0
IWA 5	61	Male	13	6	Anomic	192	Mild	Mild	Sev	Mild	80.0	91.0
IWA 6	63.7	Female	18	18	Anomic	143	Mild	Sev	Sev	Mild	13.3	67.7
IWA 7	65.7	Female	18	41	Bro.	120	Mild	Sev	Sev	Mild	0	28.4
IWA 8	69.5	Male	21	27	Wern.	78	Mild	Sev	Mild	WNL	0	33.8
IWA 9	77.2	Female	16	94	Anomic	200	WNL	WNL	WNL	WNL	98.3	98.0
IWA 10	86.8	Male	12	13	Anomic	185	Mild	Mod	Mild	Mild	58.3	88.1
IWA 11	51.9	Male	11	260	Anomic	175	Mod	Sev	Mild	Mild	31.7	61.3
IWA 12	59.5	Male	19	26	Anomic	178	WNL	Mod	WNL	WNL	78.3	82.8
IWA 13	61	Male	16	45	Con.	168	WNL	WNL	WNL	WNL	43.3	67.9
IWA 14	63.6	Female	16	64	Anomic	174	WNL	Mod	Mod	WNL	30.0	69.1
IWA 15	67.5	Female	12	28	TCM	179	Mod	Sev	Mod	Sev	83.3	82.2
IWA 16	68	Male	19	13	Anomic	74	Mild	Mild	Mod	Mild	30.0	74.3
IWA 17	47.7	Male	16	86							81.7	
IWA 18	71.9	Male	18	15	Con.	139	WNL	Mild	WNL	WNL	85.0	76.7
Cn 1	57.6	Female	18									
Cn 2	57.7	Female	18									
Cn 3	57.2	Female	16									
Cn 4	59.7	Female	16									
Cn 5	69.5	Male	16									
Cn 6	70	Male	18									
Cn 7	72.6	Female	16									
Cn 8	58.7	Male	16									

Note. Ed. = education in years; MPO = months post onset of stroke; BNT = Boston Naming Test (Kaplan, Goodglass, & Weintraub, 1983); AQ = aphasia quotient of the Western Aphasia Battery (WAB; Kertesz, 1982; higher scores represent lower degrees of aphasia severity); IWA = individual with aphasia; Cn = control.

[a]Aphasia type = conduction (Con.), Wernicke's (Wern.), Broca's (Bro.), and transcortical motor (TCM). [b]Comp. = comprehension as determined by the WAB. [c]Att. = attention, Mem. = memory, Exec. = executive functions, and Visuo = visuospatial skills as determined by the Cognitive Linguistic Quick Test (Helm-Estabrooks, 2001). CLQT scores are within normal limits (WNL), mild, moderate (Mod), or severe (Sev).

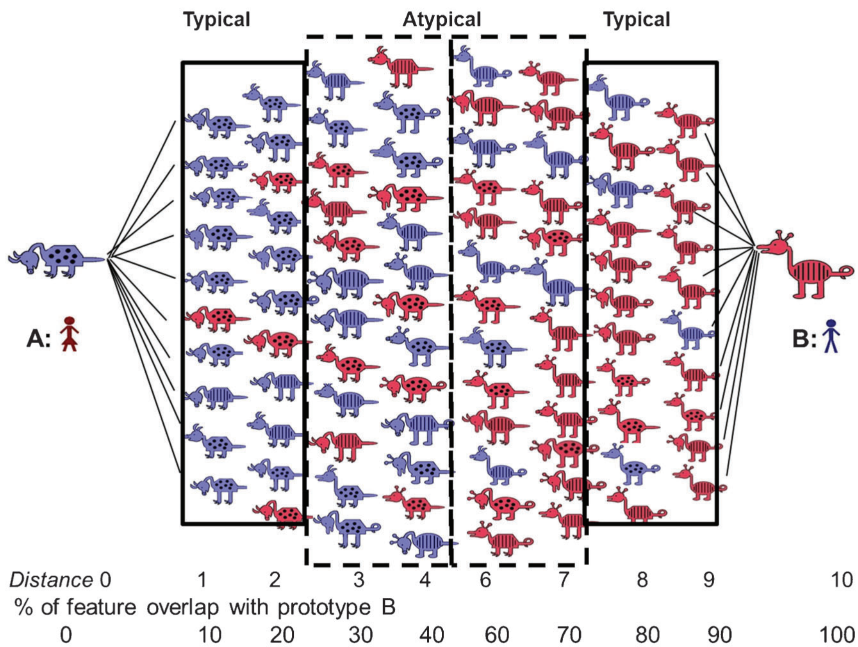
Category membership was delineated by the percentage of features that were shared with each of the two prototypes. All animals that shared at least six features with a prototype (60% feature overlap) were considered members of that category. Animals that were at distance 5 were not considered members of either category and were expected to be categorized with each of the two prototypes with a rate of 50%. 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 1).

Design and Procedures

Testing was completed in a quiet room at Boston University in the presence of a speech-language pathologist (SLP) over the course of up to 6 days (one paradigm per session for the PWA and up to two paradigms per session for the controls). Tests were computer-based and were programmed using E-Prime software (Psychology Software Tools, n.d.). The PWA completed the WAB, the Boston Naming Test (BNT; Kaplan, Goodglass, & Weintraub, 1983), and the Cognitive Linguistic Quick Test (CLQT; Helm-Estabrooks, 2001), all of which are standardized cognitive–linguistic measures.

Both the PWA and the controls completed category-learning tasks for which instruction method was either FB or 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, and PA Atyp. One person with aphasia dropped out after completing only three out of four tasks. Each category-learning paradigm consisted of a 10-min training phase followed by a 10-min testing phase and is described in further detail in the following paragraphs. Of note, before completing these four category-learning paradigms, each participant completed a baseline FB task and a baseline PA task, as reported in Vallila-Rohter and Kiran (2013) and also briefly described in the following paragraphs. Results from the current study were interpreted independently and within the context of baseline tasks. Stimulus sets and learning tasks were counterbalanced across participants, and paradigms were built such that no animal was repeatedly presented across paradigms (see Figure 2 for a possible sequence of tests). At the start of testing, an SLP used illustrated pictures to explain the tasks to the participants. The participants were told that they would be completing multiple paradigms, each requiring them to learn

Figure 1. Sample animal stimuli contributed by Zeithamova, Maddox, and Schnyer (2008). Animals are arranged according to the number of features with which they differ from each prototypical animal. The number of features by which an animal differs from each prototype is referred to as its distance from the prototype. Typical animals share 80% to 90% of their features with prototypes. Atypical animals share 60% to 70% of their features with prototypes.



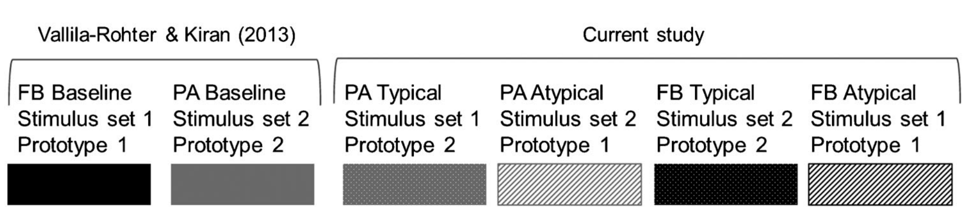
to recognize animals as belonging to one of two families. The participants were informed that each task would have a similar overall structure, but that each was unique.

In FB learning, pictures of the animals were presented one at a time on a computer screen for 4,000 ms. The participants were required to guess each animal's affiliation, indicating their selection with a left-handed button press, *1* or *2,* corresponding to categories A and B, respectively. If the participants did not respond within the 4,000-ms time frame, a message appeared indicating that they had responded too slowly. The participants received feedback for 3,000 ms after each trial that indicated the correct category affiliation and whether their response was correct or incorrect. Animals remained on screen for a total of 7,000 ms. This design encourages gradual trial-by-trial learning through feedback.

In PA learning, pictures of the animals were presented one at a time, this time with a label denoting their category affiliation. In each trial, the participants were instructed to press the button that matched the indicated category as soon as the picture appeared on the screen. The overall structure and timing of the FB task was maintained in the PA condition. The animals remained on screen for 7,000 ms and were followed by a 1,000-ms fixation cross before advancing to the next animal. This design supports the formulation of stimulus response associations.

The FB and PA instruction paradigms were similarly structured and started with a 10-min training phase

Figure 2. Sample sequence of testing. All participants completed baseline tasks followed by the completion of four additional category-learning tasks. Task instruction, typicality, stimulus set, and prototype were counterbalanced across participants.



consisting of 60 categorization trials. Prototypes were never presented in training. Within these parallel task structures, we constructed two training conditions: typical and atypical. 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 (animals that had a 60% to70% 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 three to six times with the opposite category. This condition was created in order to emphasize typical category features, increasing their salience through training. Under atypical training conditions, overall task structure was maintained, the only manipulation being that the 60 stimulus animals presented in training were all atypical to categories. Participants therefore saw each feature associated 15 to 21 times with one category and nine to 15 times with the opposite category. This condition was created in order to emphasize the feature variability of categories. Vallila-Rohter and Kiran's (2013) FB baseline and PA baseline tasks were similarly structured to these paradigms; however, in the baseline conditions, the 60 stimulus items presented in training included both typical and atypical exemplars.

All training paradigms were followed by a 72-trial testing phase. Following all training conditions, the participants were tested on their categorization of prototypes, typical and atypical items. We were interested in examining participants' abilities to learn not only animals within the 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. Test items included novel animals and animals that had been seen in training. In this phase, the animals appeared one at a time on a computer screen and participants were given 4,000 ms to indicate each animal's category affiliation with a button press. No feedback was provided. Testing phases were identically structured following all conditions. Data were collected on accuracy and reaction time, although at this time, only accuracy data are reported and analyzed. Accuracy rates were examined to determine whether the participants learned overall category structure across tasks.

Research has shown a tendency for participant responses to probability match stimulus characteristics during probabilistic learning (Knowlton et al., 1994). Therefore, for our experimental tasks, we predicted successful learning to correspond to responses that matched the percentage of feature overlap with prototypes (i.e., animals at distance 1 would be categorized with prototype B in 10% of trials and with prototype A in 90% of trials). This prediction is further supported by results of our previous study (Vallila-Rohter & Kiran, 2013). We predicted the percentage of B response (%BResp) scores to increase by 10% with each ordinal increase in distance from prototype A. Thus, successful learning of the category corresponds to a linearly increasing %BResp with a slope of +10. Chance response would produce 50% BResp across all distances from the prototype, corresponding to a slope of 0.

This model also allows us to probe the question of generalization from atypical items to typical items following training. In order to produce %BResp scores that satisfy our conditions for learning following atypical training, participants must produce categorizations with a high probability match for typical exemplars and prototypes. Therefore, successful learning following atypical training necessitates 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 are unable to measure generalization from typical to atypical items.

Data Analysis

For each participant, mean accuracy scores at each distance from prototype A were first converted into a %BResp score. This allowed us to examine responses and trends as a function of distance from prototype A. Once scores were converted to a %BResp score at each distance, we analyzed overall performance using a mixed model analysis of variance (ANOVA) with typicality (Typ vs. Atyp) and instruction method (FB vs. PA) as within-subject factors and group (PWA vs. controls) 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. In order to do this, we tested scores for linearity and also examined slopes of %BResp with increasing distance. As described above, correct probability matching on our task corresponds to a linearly increasing %BResp with a slope of +10. Scores were tested for linearity using a method described by Cox and Wermuth (1994) and Gasdal (2012). In this method, three model regressions with different independent variables are compared. For our task, the three modeled independent variables were our distance term, the square of our distance term, and the cube of our distance term. In order to satisfy conditions of linearity, %BResp scores had to produce a significant regression between %BResp and our distance term with an alpha value $<.05$ that was also the greatest significance value across models. We computed a linear regression coefficient for each result. Each participant was assigned a score of learning (slope) for each training condition based on linear coefficients. Using these analyses, we were able to examine the patterns of learning across conditions for the PWA and controls.

Finally, we used regression analyses to explore relationships between PWA 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 FB Typ, FB Atyp, PA Typ, and PA Atyp training. Four additional linear regressions were run, this time evaluating PWA slope scores of learning and standardized measures of cognitive linguistic ability. In these regressions, we explored AQ, attention, memory, executive function, and visuospatial skills as determined by composite scores on the CLQT.

Results

Our 2 × 2 × 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 the PWA 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 nonsignificant, $F(1, 23) = 0.46$, $p = .50$, suggesting that stimulus typicality influenced the performance of both PWA and controls. There was no significant main effect of instruction method, $F(1, 23) = 0.13$, $p = .72$. Thus, results do not suggest an advantage of one method of instruction over another, FB or PA. Similarly, the interaction between instruction method and group was nonsignificant, $F(1, 23) = 0.32$, $p = .57$.

Slope scores for all four test conditions and for baseline conditions for the PWA and controls are provided in Table 2. Slope scores marked with an asterisk indicate scores that satisfied our conditions of linearity and produced significant positive regression results. Figure 3 shows sample plots of %BResp as a function of distance in which a linearly increasing %BResp with a slope approaching 10 is evident.

An examination of individual control results revealed that six out of eight controls were able to successfully learn categories under every condition: 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 2 and Figure 4a).

Upon examination of individual patient results, we found that nine out of 18 PWA were able to learn categories under at least one atypical training condition. All nine of these PWA were also able to learn categories successfully following at least one typical training condition, FB or PA. We examined the performance of these PWA on our previously published baseline conditions (Vallila-Rohter & Kiran, 2013) and found that of the nine PWA who learned following at least one atypical training condition, six also demonstrated successful learning of at least one baseline task.

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

Table 2. Study participants' slope scores at baseline and following feedback-based (FB) and paired-associate (PA) training on typical (Typ) and atypical (Atyp) items.

Participant	FBBaseline	PABaseline	FBTyp	FBAtyp	PATyp	PAAtyp
IWA 1	10.26*	–9.07	10.41*	10.84*	10.10*	–8.29
IWA 2	9.48*	8.29*	8.75*	6.73*	9.61*	–1.04
IWA 3	7.66*	–9.46	9.89*	10.11*	9.719*	9.59*
IWA 4	9.48*	7.96*	8.48*	–5.96	10.74*	–6.6
IWA 5	–1.9	9.57*	9.35*	–1.5	0.06	9.35*
IWA 6	–7.32	5.15*	0.88	–5.96	8.01*	8.48*
IWA 7	–9.74	9.81*	10.00*	8.98*	–10.11	9.00*
IWA 8	6.71*	6.06*	10.21*	1.07	–4.03	4.26
IWA 9	1.95	4.87*	10.52*	9.09*	11.21*	8.01*
IWA 10	3.94	7.84*	5.14*	2.08	4.74*	8.27
IWA 11	–3.33	–2.45	11.39*	6.10*	6.88*	–4.61
IWA 12	–0.52	1.91	9.72*	2.48	8.79*	–1.99
IWA 13	–0.78	–4.37	10.23*	–5.76	3.92	1.69
IWA 14	2.27	–1.04	–0.96	0.76	11.47*	1.86
IWA 15	–1.17	*3.4*	–2.36	–4.08	–7.42	
IWA 16	2.55	–2.66	7.58*	–2.93	–1.77	2.77
IWA 17	–1.17	*1.93*	10.61*	–6.21	9.61*	–7.51
IWA 18	–0.52	–0.76	10.61*	–6.212	3.333	8.29*
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*

Note. Slope scores marked 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.

Figure 3. Sample plots of %BResp as a function of distance for two control participants. Solid lines represent results for the typical training condition, and dotted lines reflect results from the atypical training condition.

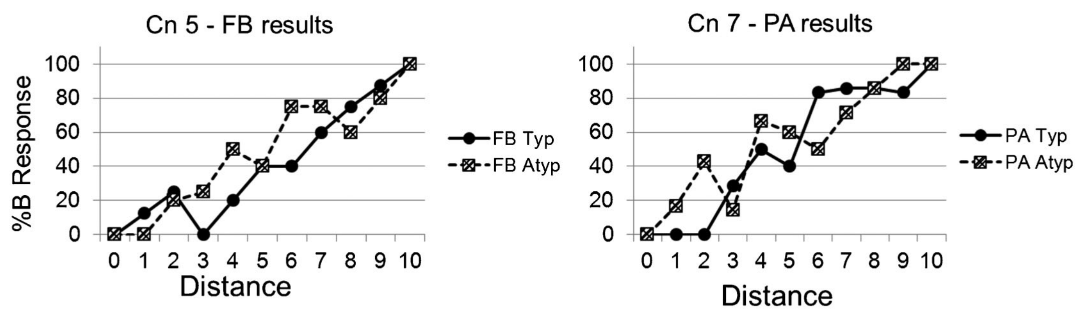
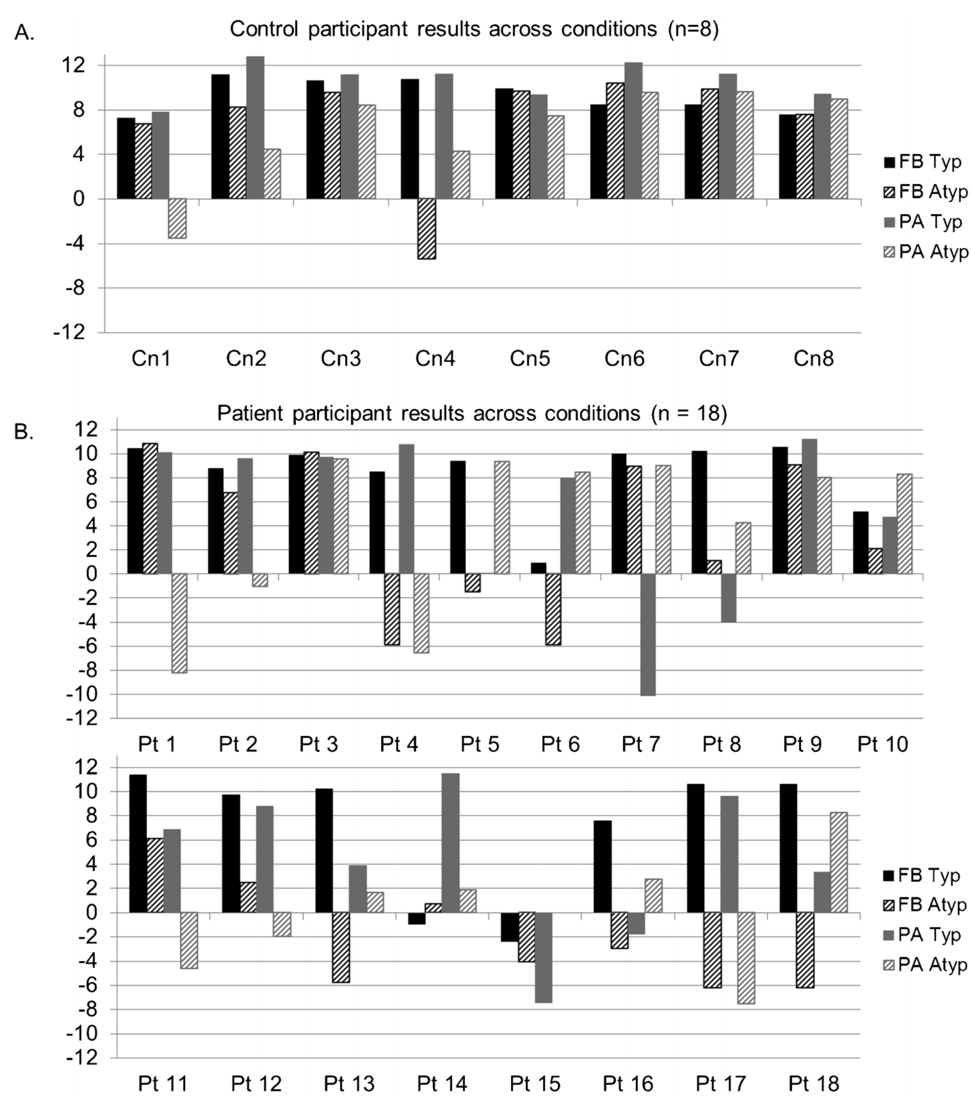


Figure 4. Slope scores of learning across tasks for control participants (top panel, A) and for patient participants (lower panels, B).



Our 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 3). Results from all other regressions of demographic measures and slope scores of learning in FB Typ, FB Atyp, PA Typ, and PA Atyp conditions were nonsignificant. Similarly, all linear regressions between slope scores and cognitive–linguistic measures of AQ, attention, memory, executive function, and visuospatial skills were nonsignificant (see Table 3).

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 nonlinguistic category learning ability of PWA and a control group of nonaphasic individuals. We compared FB and PA instruction on a multidimensional category-learning task; conditions that researchers have posited might differentially engage learning systems through the course of learning. We posited that PWA would learn better under FB conditions, as researchers have found improved information integration learning under FB conditions (Ashby et al., 2002).

For both the PWA and controls, overall learning ability was similar under FB and PA 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. The probablistic multifeature characteristics of our category likely precluded the use of a rule-based strategy. We suspect that successful learning on our task requires instance memory and automatic processes under both instruction paradigms. Feedback presence or absence likely influenced strategy use, but overall was not facilitative or disruptive.

Results suggest that when PWA are able to successfully learn categories, they can do so under either FB or PA conditions. These findings are in line with results from our previous study (Vallila-Rohter & Kiran, 2013). Unlike in PD and amnesia, foci of neural damage in aphasia are in language areas and not in regions that are critical to learning and memory. We suspect that like the controls, PWA can engage explicit or automatic processes throughout learning. Specific learning methods may be more effective for certain individuals with aphasia, but these were not identified in the current study.

Our second stimulus factor of interest, stimulus typicality, did significantly impact performance on our tasks.

Table 3. Regression results exploring the slope scores and the patient demographic and linguistic variables.

Dependent variable	Independent variable	B	Standard error (of B)	β	Significance
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
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

**$p < .01$.

Overall, we found that the typical training condition facilitated learning for all participants—both PWA and controls. 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, reducing 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 controls demonstrated 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 the controls were able to successfully extract category information in a short period of time despite high task demands.

For our participants with aphasia, 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 PWA also learned under baseline conditions. We propose that these participants have robust category-learning mechanisms that allowed them to recognize and track patterns efficiently. In contrast, 50% of the PWA were able to successfully learn only under the typical training condition. These participants did not demonstrate the ability to extract central category tendencies from atypical training items, and in addition, generally did not successfully learn under baseline conditions. Thus, for seven of the 18 PWA, learning was only successfully achieved when instruction highlighted feature overlap within categories. For these participants, an emphasis on central category tendencies proved critical to successful learning. We propose that for these participants, 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 slope scores in the PA Atyp condition were significant. Standardized measures of the WAB and CLQT did not predict success with our task. We propose that nonlinguistic category learning tasks represent a unique cognitive measure that has not yet been captured through standardized tests of aphasia. Furthermore, we hypothesize that the aphasia-inducing strokes that each of our PWA experienced may have differentially affected their learning and language networks. Some patients may have severe language deficits within the context of a relatively preserved system for category learning. Others may experience mild language deficits within a more significantly impaired category-learning network. It is also possible that current results are reflective of different premorbid learning abilities in our study participants.

Clinically, our results demonstrate differential category-learning abilities among PWA. Category learning depends on the ability to detect and integrate commonalities or patterns and is considered essential toward 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 PWA may have difficulty engaging in such integrative processes. We do not suggest that these PWA 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 PWA may experience difficulty in the process of integrating commonalities across stimuli.

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

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

We are limited in our predictions, as the current study involved a limited group of participants with heterogeneous profiles of aphasia. Also, we can only infer that skills demonstrated on our nonlinguistic category-learning task will translate to performance in actual language treatment. The next step will be to test whether predictions drawn from short, controlled nonlinguistic tasks can translate to progress with treatment. In addition, there are a multitude of demands posed on patients during regular aphasia treatment that merit to be the focus of future studies.

We do propose that current results draw attention to underlying processes that have not yet been the focus of research in aphasia, yet likely contribute to outcomes with treatment. A better understanding of how these mechanisms of learning are affected in PWA and the contribution of these processes to treatment is critical for the selection of appropriate tasks and targets for PWA. We suggest that only with a better understanding of the factors that contribute to successful learning in PWA can clinicians tailor treatment to individuals, selecting targets and methods of treatment that will facilitate patient progress and improve the predictability of patient outcomes.

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