The Effects of Frequency, Distribution, and Mode of Presentation on Learning an Artificial Language

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The study presents results from a series of experiments investigating adult learning of an artificial language and the effects that input frequency (high vs. low token frequency), frequency distribution (skewed vs. balanced), and presentation mode (structured vs. scrambled), have on such learning. Motivated by cognitive and usage-based accounts of language and learning, the research aims to contribute to theoretical debates concerning the influence of input properties in language learning. The artificial language used in the experiments is focused on the learning of noun classes modeled on Nilo-Saharan languages. Two artificial noun classes, each with distinct morphological features, were devised based on a semantic contrast between entities that are typically encountered as individuals and those typically encountered as groups, sets, pairs or masses. In each experiment, subjects were exposed to words and pictures representing the two noun classes. The learning phase was followed by a testing phase to assess their learning with respect to both trained and previously unseen exemplars of each class. The results show that presentation mode had the largest effect on learning, followed by token frequency and frequency distribution. These findings contribute new knowledge to our understanding of the learning of functional morphology—which has been viewed as a major theoretical challenge by researchers working within such diverse perspectives as the processing-instructional paradigm and generative SLA—and leads to pedagogical implications that may benefit learners.

The roles of frequency, frequency distribution, and input modification in acquisition of grammatical morphemes

The role of input frequency in the acquisition of morphology is an issue that was initially explored in a series of studies by Larsen-Freeman (1975, 1976, 1978), showing that frequency may play a significant role with respect to the order of acquisition of grammatical morphemes in English, and has been more extensively discussed recently by SLA researchers who subscribe to usage-based account of language and language learning (e.g., Boyd & Goldberg, 2009; Collins & Ellis, 2009). In her investigation of 24 ESL learners' performance, Larsen-Freeman (1975) found that the subjects' performance on English morpheme acquisition did not completely conform to the L1 morpheme acquisition order reported in Brown (1973) and attempted to provide a number of possible explanations with respect to the SLA order, which she referred to as a difficulty or accuracy order. Although Brown had rejected input frequency as an explanation for the L1 order of acquisition, Larsen-Freeman concluded that input frequency was the most significant predictor of several factors that she considered, as determined by significant positive correlations between the L2 accuracy order and the input-frequency order in parental speech that was reported by Brown (1973) and also later corroborated by significant positive correlations with the frequency of the morphemes in ESL teacher-talk (Larsen-Freeman, 2002). Regarding the effects of input frequency, Ellis (1996, 1998, 2002, 2008) has argued that second language learning is input driven and that for learners to successfully notice particular language usage events, input frequency has an important role in registration and storage in memory. Input frequency means the frequency of linguistic forms, which counts how often a particular linguistic form occurs in the input (i.e., token frequency of a particular word, morpheme, or larger construction). As Schmidt (1994) has argued, conscious registration ("noticing") is particularly important in second language learning, and high frequency morphemes are likely to be noticed earlier than low frequency morphemes. Explicit registration of second language usage events with high frequency should be beneficial, whether the conscious processes are initiated voluntarily (Schmidt, 1990, 1993, 1994, 1995,

2001) or by instruction (Norris & Ortega, 2000). For these and other reasons, frequency is considered to be a necessary component of theories of language processing and a major driving force behind language learning (Ellis, 1998; Larsen-Freeman, 1997, 2002; MacWhinney, 1997, 1999).

Within the cognitive linguistics literature, Bybee (1985, 1988, 1995, 2006, 2007, 2010) has proposed a usage-based network model of morphology, which emphasizes the role of type as well as token frequency. Type frequency is determined by how many different lexical items fill in slots in a particular construction. For example, the past tense verb pattern formed by a vowel change from /I/ to /æ/ (e.g., *sing*: *sang*, *ring*: *rang*) occurs with only a few verbs (low type frequency), although these individual verbs are quite high in occurrence (high token frequency). Bybee (2010) argues that patterns that are high in type frequency in the input are reinforced, and become more productive. On the other hand, patterns that are low in type frequency are weaker, and become less productive. Bybee hypothesizes that the forms that are high in token frequency are learned faster, but as the individual token frequency decreases, type frequency, the patterns associated with the interconnections among meaning and forms, come to play an important role in learning.

Besides token and type frequency, usage-based accounts of language learning suggest that frequency distribution can also have an effect on construction learning. Ellis and Ferreira-Junior (2009) and Boyd and Goldberg (2009) identify skewed distribution—a low variance distribution in which prototypical exemplars appear in high frequency—to be a potential determinant of learning. Natural linguistic corpora demonstrate that the most frequent word occurs approximately twice as often as the second most frequent word, three times as often as the third most frequent word, etc. Goldberg, Casenhiser, and White (2007) argue that this skewed distribution in language use may have a significant impact on learning constructions. The fact that words are distributed in skewed fashion restricts overall input variability, indicating that learners tend to hear the same set of words repeatedly in the same construction types. The hypothesis that follows is that the presence of prototypical exemplars in skewed input distribution may facilitate construction learning by making the meaning and form connection of a particular construction easier to identify.

Recent research also suggests that structured (as opposed to randomly scrambled) input has facilitative effects on construction learning. Arguments in favor of structured input can be found in the literature on instructed SLA (VanPatten, 2002, 2004), some generative approaches (Lardiere, 2007; Slabakova, 2003, 2005, 2008), and in the literature on statistical learning in psychology and psycholinguistics (Onnis, Waterfall, and Edelman, 2008). Onnis, et al. (2008) investigated how structurally distributed input affects learners' inference of regularities in an artificial language, suggesting that the combination of temporal contiguity, input contingency, and semantic contrast in structured input is the key factor in learning processes and that the order of presentation in the input can make a significant difference in learning outcomes. The processing-instructional paradigm in SLA (DeKeyser, 2005; VanPatten, 2002, 2004) provides additional arguments and sources of predictions about structured input. Generative SLA (Lardiere, 2007; Slabakova, 2003, 2005, 2008) can also be seen as providing some rationale for the structured input condition on the acquisition of second language morphology.

Although understanding of the learning of functional morphology has been viewed as a major theoretical challenge by SLA researchers, empirical investigations on the issues regarding input frequency are under-researched, and the study takes these topics as the research questions and investigates the effects of token and type frequency interaction and skewed input on the learning of functional morphology in an artificial language. Also, research in instructed SLA, generative grammar, and statistical learning all point to the benefits of structured rather than randomly scrambled input. Since the arguments for these benefits have recently emerged in the literature, more research is needed to ascertain the effects of structured input for SLA. The study addresses this question asking whether temporal congruity and semantic contrast in the input facilitate lexical and morphological learning in an artificial language.

Research questions and hypotheses

RQ1. Does token frequency have an effect on the process of learning nominal morphology when type frequency is held constant?

RQ2. Does frequency distribution (skewed vs. balanced) have an effect on the process of learning nominal morphology?

RQ3. Does mode of presentation (structured vs. scrambled) have an effect on the process of learning nominal morphology?

Hypothesis regarding RQ1: High token frequency in input (the total number of occurrences in input of particular nouns or nouns of a particular class) will have a facilitative effect on the process of learning nominal morphology when type frequency (the number of lexical items that can occur in a particular construction) is held constant. This hypothesis is motivated by the suggestion in previous studies that nouns with high token frequency draw learners' attention and aid subsequent storage in memory (Ellis 2002; Ellis & Schmidt 1997, 1998).

Hypothesis regarding RQ2: Skewed distribution in input (input containing a small number of high frequency prototypical exemplars) will be more facilitative than balanced distribution in input (even distribution of prototypical and non-prototypical exemplars) on the process of learning nominal morphology. The rationale for this hypothesis derives from the admittedly rather limited findings in previous studies that the presence of prototypical exemplars in skewed input distribution facilitates construction learning and the suggestion that this may happen because skewed input makes meaning and form connections simpler to identify (Casenhiser & Goldberg, 2005).

Hypothesis regarding RQ3: Structured input (input in which the uninflected and inflected forms of nouns are presented consecutively in pairs) should be more facilitative than scrambled input (input in which forms of nouns are randomly presented) on the process of learning nominal morphology. It is hypothesized that presenting consistent pairing of nominal constructions and world referents in a temporally neighboring manner facilitate identification of the constructional schemas and their semantic consistency, making both semantic and formal distinctions salient to learners. The rationale for this hypothesis derives from the discussions of the benefits of structured input in previous research that learning proceeds depending on the relevant relations that learners find in temporal contiguity and semantic contrast presented in the input (Onnis, et al., 2008).

Method

Two experiments were conducted. Experiment 1 investigated the effect of token frequency on learning (RQ 1); Experiment 2 compared conditions of skewed vs. balanced input (RQ 2) and conditions of structured vs. scrambled input (RQ 3). A total of 150 participants were recruited for the study. For the experiments, a miniature artificial grammar was created consisting of 20 nouns. Modeled loosely on Nilo-Saharan languages, the two noun classes devised for the experiments were motivated by the semantic distinction, grounded in real world experience, between physical entities that are typically encountered as individuals and those typically encountered as groups, sets, pairs or masses. After consulting a number of linguistic and semantic analyses of noun classes and nominal morphology (Allan, 1980; Croft, 2000; Wierzbicka, 1988), two noun classes were devised for use as an artificial grammar, combining formal structures and semantic features. Noun Class 1 comprises nouns referring to physical entities that are typically encountered as individuals. Table 1 shows the semantic basis, forms and corresponding construals of Noun Class 1.

Table 1. ***Noun Class 1***

Semantic Basis	Entities Typically Encountered as Individuals
Form	Bare Stem
Construal	Individual
Form	Inflected - prefix *ku*
Construal	Aggregate

The bare stem of nouns in the Noun Class 1 construes the entity as a particulate individual, while the inflected form, using the prefix *ku* construes the entity as an aggregate or more than one, i.e. a plural. Thus, in Noun Class 1, there are two related constructions, the bare-stem construction (with an individual construal) and the *ku*-construction (with an aggregate construal).

Noun Class 2 consists of nouns referring to physical entities that are typically encountered as groups, sets, pairs or masses. Table 2 shows the semantic basis, forms and corresponding construals of Noun Class 2.

Table 2. ***Noun Class 2***

Semantic Basis	Entities Encountered in Groups, Sets, Pairs and Masses
Form	Bare Stem
Construal	Whole
Form	Inflected - prefix *bu*
Construal	Individuated

The bare stem of nouns in Noun Class 2 construes an entity as an unidividuated whole**,** while the inflected form, with a *bu* prefix, construes the entity as individuated. Like Noun Class 1, Noun Class 2 consists of two related constructions: the bare-stem construction (with a whole construal) and the *bu*-construction (with an individuated construal). Artificial words were then created to constitute the lexicon used in the subsequent main experiments.

All participants took a web-based language training session on a web browser. In the training session, participants saw a series of pictures matched with artificial words on the computer screen. Throughout the training session, the participants' task was to type the word in a block provided, then click the “next” button. The learning session took approximately 25 minutes to complete. Participants were exposed to a total of 24 unique word forms (72 tokens) during the training. After the training session, each participant took a word recognition test consisting of 32 items. For each item, the participants answered whether the artificial word they saw on the computer screen matched the picture.

In order to ascertain whether or not participants in these experiments successfully learned the target constructions of Noun Class 1 and Noun Class 2, immediately following the training, subjects were presented with 32 pictures and words and asked to judge in each case whether the picture-word match that was shown was correct or incorrect. All of the test items had true-false item format, and they were presented via a computer screen. Each participant was asked to click "yes" button on the computer screen if they saw a correct match between the word form and the picture or "no" button if they saw a mismatch.

Analyses

The design of the analysis for Experiment 1 and Experiment 2 was factorial multivariate analysis of variance. For Experiment 1, comparisons were made using token frequency (high vs. low) as a between subject factor. For Experiment 2, comparisons were made using input distribution (skewed vs. balanced), and mode of presentation (paired vs. single) as between subject factors. For inferential statistics, four subtests were prepared. The first two subtests were used to assess how well subjects learned the items belonging to Noun Class 1 and Noun Class 2 that they had been exposed to in the training phase. The other two subtests were used to assess how well subjects could generalize their knowledge to new words belonging to these two noun classes that they had not seen in the training. The same sets of items were used for Experiment 1 and Experiment 2. The effect sizes of independent factors in Experiment 1 and Experiment 2 were estimated. For each learning condition in Experiment 1 and Experiment 2, descriptive statistics, and reliability (Cronbach's alpha) were calculated.

Results

The overall reliability (Cronbach's alpha) for all experimental conditions was 0.85. Cronbach's alphas for the second condition in Experiment 1 (0.87), the baseline (0.91), and the skewed input (0.86) conditions in Experiment 2 all showed reasonably good internal consistency. The participants' response accuracy for the test items was coded using 1 for correct and 0 for incorrect responses. These binary data were then transformed into *d′* prime statistics (Macmillan & Creelman, 1991), calculated using the following formula:

$$d' = (\text{z transform of correct response rate}) - (\text{z transform of false alarm rate})$$

Z transforms of these two rates (correct response minus false alarm rates) were calculated using the inverse of the normal distribution function. The statistic *d′* indicates the distance between the correct response rates and false alarm rates. The larger the difference between correct response and false alarm rates, the better the subject's response accuracy. When the correct response rates and false alarm rates are the same, *d′* = 0. The highest possible *d′* (greatest response accuracy) is 6.93, and the lowest possible *d′* (worst response accuracy) is - 6.93. The highest effective limit (using 99% for probability of responce accuracy) is 4.65. The lowest effective limit (using 1% for probability of responce accuracy) is - 4.65. Typical values vary from - 2.0 to 2.0. For instnace, *d′* of 1.0 corresponds to 69% correct response accuracy while *d′* of - 1.0 corresponds to 31% correct response accuracy.

For inferential statistics, four subtests were prepared. The first two subtests were used to assess how well subjects learned the items belonging to Noun Class 1 and Noun Class 2 that they had been exposed to in the training phase. The other two subtests were used to assess how well subjects could generalize their knowledge to new words belonging to these two noun classes that they had not seen in the training. As a result, the variables for the experiments had the following 4 independent scores:

1. *d′* prime statistics for the trained items of Noun Class 1
2. *d′* prime statistics for the generalization items of Noun Class 1
3. *d′* prime statistics for the trained items of Noun Class 2
4. *d′* prime statistics for the generalization items of Noun Class 2

Experiment 1 was designed to investigate the effect of token frequency (RQ 1) on learning the noun classes and constructions of the artificial language. In order to address these questions, the aforementioned accuracy response data were submitted to a factorial MANOVA.

The alpha level for the MANOVA was set to 0.05. The MANOVA results indicated that the main effect of frequency condition (Wilks' Lambda = 0.492, $p < 0.001$) was statistically significant on the linearly combined dependent variables (trained items of Noun Class 1, generalization items of Noun Class 1, trained items of Noun Class 2, and generalization items of Noun Class 2) by all participants. The effect size of Frequency was 50.8 % of the total variance, and the statistical power (0.99) was adequate to reject the null hypothesis. Descriptive statistics were also computed with respect to the results of each dependent variable (trained vs. new words, Noun Class 1 and Noun Class 2). Follow-up ANOVA was subsequently carried out with respect to the effects of frequency. When focused on the effects of frequency on each measure by all participants, the results showed that the largest effects were on the trained items of Noun Class 1, $F\ (1, 56) = 13.00$, $p < 0.001$, $\eta p^2 = 0.19$, and on the generalization items of Noun Class 1, $F\ (1, 56) = 12.00$, $p < .001$, $\eta p^2 = 0.18$, followed by the effect on the trained items of Noun Class 2, $F\ (1, 56) = 7.48$, $p = .008$, $\eta p^2 = 0.12$. The frequency effect on the generalization items of Noun Class 2 was not statistically significant, $F\ (1, 56) = 3.36$, $p = 0.72$, $\eta p^2 = 0.06$. On the trained items of Noun Class 1, the effect size of Frequency was 19 % of the total variance, and the statistical power (0.94) was adequate to reject the null hypothesis. On the generalization items of Noun Class 1, the effect size of Frequency was 18 % of the total variance, and the statistical power (0.93) was also adequate to reject the null hypothesis. On the trained items of Noun Class 2, the effect size of Frequency was 12 % of the total variance. However, the statistical power (0.78) did not reach the adequate value (0.8) to reject the null hypothesis.

Experiment 2 was designed to investigate the effects of frequency distribution (RQ 2) and mode of presentation (RQ 3) on learning the noun classes and constructions of the artificial language. In order to address these questions, the accuracy response data were submitted to a factorial MANOVA. The alpha level for the MANOVA was set to 0.05. The MANOVA results showed that the main effects of input condition (Wilks' Lambda = 0.542, $p < 0.001$) were statistically significant on the linearly combined dependent variables (trained items of Noun Class 1, generalization items of Noun Class 1, trained items of Noun Class 2, and generalization items of Noun Class 2) by all participants. The effect size of input condition was 26.4 % of the total variance, and the statistical power (0.99) was adequate to reject the null hypothesis. The alpha level for the follow-up ANOVAs was adjusted using Bonferroni corrections with respect to the number of planned comparisons. The effect of input (Balanced, Skewed, Structured) on each measure by all participants was statistically significant on all dependent variables—the trained items of Noun Class 1, F (2, 84) = 16.27, $p < 0.001$, $\eta p^2 = 0.28$, the generalization items of Noun Class 1, F (2, 84) = 9.33, $p < 0.001$, $\eta p^2 = 0.18$, the trained items of Noun Class 2, F (2, 84) = 12.62, $p < 0.001$, $\eta p^2 = 0.23$, and the generalization items of Noun Class 2, F (2, 84) = 15.25, $p < 0.001$, $\eta p^2 = 0.27$. On the trained items of Noun Class 1, the effect size of input was 28 % of the total variance, and the statistical power (0.99) was adequate to reject the null hypothesis. On the generalization items of Noun Class 1, the effect size of input was 18 % of the total variance, and the statistical power (0.97) was adequate to reject the null hypothesis. On the trained items of Noun Class 2, the effect size of input was 23 % of the total variance, and the statistical power (0.99) was adequate to reject the null hypothesis. On the generalization items of Noun Class 2, the effect size of input was 27 % of the total variance, and the statistical power (0.99) was also adequate to reject the null hypothesis.

For the trained items of Noun Class 1, the effects of structured input were statistically significant. Participants in the structured condition significantly outperformed their counterparts in the baseline condition. On the other hand, the effects of skewed input were not statistically significant. For the generalization items of Noun Class 1, the effects of input were not statistically significant for any comparisons. For the trained items of Noun Class 2, the effects of input were evident.

Participants in the structured condition significantly outperformed the participants in the baseline condition (Mean difference = 1.845, $p < 0.001$, 95% CI for mean difference = 0.920 ~ 2.771). On the other hand, the participants in the skewed input condition did not significantly outperform their counterparts in the baseline condition (Mean difference = 1.025, $p = 0.03$). For the generalization items of Noun Class 2, input effects were statistically significant. The participants in the structured condition outperformed the participants in the baseline condition (Mean difference = 1.866, $p = 0.002$, 95% CI for mean difference = 0.684 ~ 3.047).

Discussion

Regarding frequency (Research Question 1), it was hypothesized that high token frequency (the total number of occurrences in input of nouns of a particular class) would have a facilitative effect on the process of learning both the specific nouns to which learners were exposed and the noun classes and constructions that they represent.

Results indicated that token frequency had a statistically significant effect on the linearly combined dependent variables (trained and generalization items of Noun Class 1 and Noun Class 2) by all participants. When we focus on the effects of token frequency on each dependent variable, token frequency had a statistically significant effect on both the trained and generalization items of Noun Class 1 and on the trained items of Noun Class 2. However, token frequency did not have a statistically significant effect on the generalization items of Noun Class 2.

In sum, high token frequency was found to have statistically significant effects on the trained items of Noun Class 1 and Noun Class 2. Token frequency had a strong effect especially on the trained items of Noun Class 1, indicating that 20.3% of the total variance can be explained by the frequency effect. However, it is important to note that token frequency had a limited and inconsistent effect on the generalization items of Noun Class 1 and Noun Class 2.

These findings showing that when type frequency was controlled, token frequency had a statistically significant effect on the process of learning the nouns of the artificial language overall partially support theoretical proposals regarding the role of token frequency in construction learning by Bybee (1988, 2010) and Ellis (1996, 1998, 2002, 2008). Ellis (2002) argued that high token frequency underpins conservation of particular linguistic patterns:

> the acquisition of grammar is the piecemeal learning of many thousands of constructions and the frequency-biased abstraction of regularities within them [...] Frequency is thus a key determinant of acquisition because "rules" of language, at all levels of analysis (from phonology, through syntax, to discourse), are structural regularities that emerge from learners' analysis of the distributional characteristics of the language input. (p. 144)

Bybee also (1988, 2010) emphasizes the role of token frequency in construction learning:

> [...] exemplars are strengthened as each new token of use is mapped onto them, high-frequency exemplars will be stronger than low-frequency ones, and high frequency clusters —words, phrases, constructions— will be stronger than lower frequency ones [...] first, stronger exemplars are easier to access, thus accounting for the well-known phenomenon by which high frequency words are easier to access in lexical decision task. Second, high-frequency morphologically complex words show increased morphological stability (Bybee, 2010, p.24)

> [...] what language users experience is specific instances of tokens of constructions. They map similar tokens onto one another to establish exemplars and these exemplars group together to form categories that represent both the fixed and schematic slots in constructions. The

> meaning of constructions is also represented by a set of exemplars which are built up by accessing the meaning of the lexical items used [...] (Bybee, 2010, p.26)

The study findings show that high frequency constructions were learned more accurately than low frequency constructions, indicating that initial provision of nouns with high frequency is beneficial. As Bybee (2010) and Ellis (2002) have suggested, provision of high token frequency nouns underpins morphological regularity, and thus it helps learners draw their attention to the frequencies and consistencies of mappings between forms and their functions.

However, in further analyzing the learning outcomes, results showed mixed evidence regarding the relation between token frequency and construction learning. As noted above, while high token frequency had a positive effect on the trained items of Noun Class 1 and Noun Class 2, it did not show consistent effects on the generalization items of either Noun Class 1 or Noun Class 2, suggesting that token frequency alone may not been sufficient for the participants to generalize to nouns not seen during the training. Some inferences can be made based on these findings.

First, a possible explanation for this part of the findings may rest with the short-term nature of the training phase in the experiment. Generalization to new words might have occurred through exposure to more repetitive exemplars in the input. In this regard, the design of the study may not have been sufficient, and provision of the training items (five times for high frequency and once for low frequency words) may not have been enough for the study participants to successfully extend what they had learned through the short-term exposure to new words that they had not encountered in the training phase. Alternatively, the findings can be taken to suggest that token frequency works solely or primarily by fostering item-based learning and may not lead to the inductive abstraction of schemata for generalizing to new words.

The hypothesis regarding Research Question 2 predicts that skewed distribution in input (prototypical exemplars presented with high frequency and less prototypical exemplars presented less frequently) will be more facilitative than balanced distribution in input (even distribution of prototypical and non-prototypical exemplars) on the process of learning the noun classes and constructions of the artificial language. Experiment 2 used a Balanced (baseline) and a Skewed condition to test this hypothesis. In the Balanced Condition, there were no manipulations of input distribution. The distribution of prototypical and non-prototypical exemplars of each noun class was balanced, and all nouns were presented in pseudo-random order. In the Skewed Condition, the prototypical exemplars of each noun class were provided five times while the non-prototypical exemplars were provided once, all in pseudo-random order.

The skewed distribution condition had a significant positive effect on the generalization items of both Noun Class 1 and Noun Class 2 compared to the baseline. However, skewed distribution did not have a statistically significant effect on the trained items of Noun Class 1 or Noun Class 2.

When we focus on the effects of skewed distribution on each dependent variable, skewed distribution had a statistically significant effect only on the generalization items of Noun Class 2. Skewed distribution did not exhibit any statistically significant effects on the trained or generalization items of Noun Class 1 or the trained items of Noun Class 2.

In summary, compared to the effects of token frequency (which mainly had positively effects on trained but not new items), skewed distribution exhibited the opposite pattern, a positive effect on the generalization items but not trained items, suggesting that skewed distribution affects the acquisition of the noun classes and morphological constructions—not merely items or exemplars of a category—and that it is effective in the early stage of learning when a new type of construction is encountered by learners. These results are compatible with findings in previous studies that showed a facilitative role of skewed distribution in the acquisition of linguistic constructions in an artificial language (Casenhiser & Goldberg, 2005; Goldberg, Casenhiser & Sethuraman, 2004). Results also support the theoretical proposals made by researchers such as Boyd and Goldberg (2009), Collins and Ellis

(2009) and Goldberg et al. (2007). Boyd and Goldberg (2009) suggest that provision of high frequency prototypical exemplars that represent the exemplary meanings of the constructional category promote the inductive abstraction of morphological schemata by making the meaning of the construction salient to the learners.

However, in further analyzing the effects on each dependent variable, the findings showed that skewed distribution had a statistically significant effect only on the generalization items of Noun Class 2. These aspects of the findings need to be explained: the fact that the Skewed Input Condition had no effect on trained items; the fact that skewed input had a positive effect only on the generalization items of Noun Class 2 (not Noun Class 1). A possible explanation of the lack of strong and consistent results supporting claims for the advantages of skewed input might be that the skewed condition was not actually skewed enough. The relative difference in frequency between the prototypical exemplars and non-prototypical exemplars (five to one) may not have been large enough in order for the skewed input to be sufficiently effective for generalization across both noun classes and both participant groups.

The hypothesis regarding Research Question 3 predicts that structured input (in which the semantically related uninflected and inflected forms of nouns and the photographs illustrating them are presented in pairs) should be more facilitative than scrambled input (in which inflected and uninflected forms of nouns are encountered randomly) on the process of learning noun classes and constructions of the artificial language. Experiment 2 included a Scrambled Condition (baseline) and a Structured Condition to test this hypothesis. In the Scrambled Condition, there were no manipulations of the mode of presentation, and all nouns appeared three times in pseudo-random order. In the Structured Condition, 16 out of 24 nouns sharing the same root appeared in tandem (uninflected forms followed by inflected forms).

The results showed that structured input had a strong and statistically significant positive effect on all dependent variables. When we focus on the effects of structured input on each dependent variable, structured input had a statistically significant positive effect on the trained items of Noun Class 1 and Noun Class 2 and on the generalization items of Noun Class 2. Results indicated that the effects of structured input were evident on the participants' response accuracy for most of the dependent measure items. There was a strong and significant effect on the trained items. A limited but still significant effect was also found on the generalization items. These overall effects on most of the trained and generalization items suggested that provision of structured input is definitely helpful in the early stage of learning when learners encounter a new type of construction. The results also showed that structured input was effective on the ability to generalize to new members of the construction, showing that participants were not just memorizing specific nouns but were establishing representations of the constructions associated with the noun classes by their exposure to structured input. Results were compatible with the findings in previous studies that showed a facilitative role of structured input in the acquisition of linguistic constructions in an artificial language (Onnis et al., 2008) and support the theoretical proposals that point to the benefits of structured input that make the match between forms and meanings structurally and semantically transparent from generative SLA (Lardiere, 2007; Slabakova, 2003, 2005, 2008) and instructed SLA (Van Pattan 2002, 2004).

Onnis et al., (2008) argues that structurally distributed input affect learners' inference of regularities and suggested that the combination of temporal contiguity, input contingency, and semantic contrast in input is an important factor in learning. They hypothesized that construction learning advances based on the formal relations and semantic contrast that learners find in temporal contiguity in input. The findings of the current study are compatible with these predictions, indicating that encountering pairs of grammatically and semantically related nouns in a contiguous manner is beneficial, compared to a scrambled presentation of the same amount of input in which individual form-meaning pairs (individual nouns and photographs) are not presented in a way that makes salient their paradigmatic relationships.

In generative SLA, Lardiere, (2007) proposed the benefits of structured input in the acquisition of L2 morphology. Ladiere argued that what counts in acquisition of morphology in L2 is how learners can successfully detect appropriate mappings between the form and its meaning. One way to make functional morphology detectable to L2 learners is to provide minimally contrasting forms with differences in meaning to establish the relation between form and meaning. Similarly, Slabakova (2003, 2005, 2008) suggested that for L2 learners to detect functional morphology in L2, it is important to provide meaningful instances where the formal relations and the semantic import of the morphology are transparent. In the Structured Condition, exemplars in semantically related pairs with minimally contrasting forms were provided to the participants in order to address the issue of making the semantic import of the morphology transparent. Results from Experiment 2 showed the advantages of structured input over scrambled input, supporting the proposals made by Ladiere (2007) and Slabakova (2003, 2005, 2008) as well.

The current results are also compatible with the proposal from the processing instructional paradigm in SLA (VanPatten, 2002, 2004). VanPatten (2004) has pointed out the importance of structured input and argued that learners need to be exposed to both structured input and explicit instruction. VanPatten argued that the key feature of his processing instruction is the design of the structured input in which the exemplar pairs are consecutively paired and contrasted in terms of form and meaning. In addition, VanPatten reassured the importance of explicit explanation of the target constructions, assisting learners in making appropriate form- meaning associations of the target linguistic elements to be practiced, proposing processing instruction as a practical solution to the difficulty of having learners transform their understanding of L2 constructions into communicative use and that structured input can be applied to the teaching of L2 functional morphology.

As VanPatten predicted, the experiment results demonstrated the advantages of providing structured input on learning constructions. Experiment 2 reported here, however, did not provide any explicit metalinguistic explanations as part of structured input, a practice endorsed by VanPatten (2002, 2004) and opposed by others (Doughty, 2004). More research is needed in order to examine whether provision of structured input alone and input plus explicit metalinguistic explanations lead to differential learning outcomes.

Conclusion

Findings gleaned from this study contribute to an improved understanding of the learning of noun classes and functional morphology in a second language. This research aimed to examine the benefits and the relative importance of input frequency, distribution, and presentation mode. An improved understanding in this area has some practical implications for theory, research, and pedagogy.

First, the results showed that token frequency mainly had a statistically significant positive effect on the process of learning the nouns of the artificial language to which participants were exposed, showing that token frequency strongly affects the learning of the exemplars of noun classes and constructions but does not necessarily lead to generalization. Skewed distribution, on the other hand, exhibited the opposite pattern. A limited but positive effect was found on generalization to new nouns (but not on the nouns to which participants were exposed), suggesting that skewed distribution affects the acquisition generalization and establishment of schematic representations of noun classes and constructions (not merely exemplars). Third, the effects of structured input were strong and consistent on participants' response accuracy for most of the dependent measures, showing that there was a significant effect on both item learning and system learning. These overall effects of structured input suggested that participants were not just memorizing exemplars but were establishing representations of the constructions associated with the noun classes.

Issues arising from the findings of this study have some implications for theory and research regarding the roles of input and L1 in learning of L2 noun classes and the constructions associated with them. In direct contrast to the results for token frequency, where there was a significant effect on trained words and a limited and inconsistent effect on novel words, the results for skewed distribution showed no effect for the learning of trained words but an effect (although not strong and somewhat inconsistent) on construction learning. These contrasts in the findings raise a theoretical question that is whether provision of high token frequency promotes different types of learning from provision of skewed input. In this sense, the claim that provision of high token frequency nouns aids conservation of morphological patterns in memory needs to be investigated further. There is a distinction between exemplar learning and category or construction learning. Although the exemplars of the noun classes and constructions exist in the input, the noun classes and constructions themselves are mental phenomena, representations based on generalizations from data to which learners are exposed. More research is needed to scrutinize what kind of knowledge learners are likely to gain, lexical knowledge or generalizable construction knowledge, though exposure to the exemplars with high token frequency.

As for the effects of skewed input, the study provided positive evidence on category and construction learning, indicating that provision of high frequency prototypical exemplars, which represent the exemplary meanings of the constructional category promote the abstraction of morphological schemata by making the prototypical meaning salient to learners. However, the results showed that the effects were not strong and somewhat inconsistent, suggesting that although skewed distribution has some positive effects on generalizability in category and construction learning, the effects of skewed input may not be robust. It can be hypothesized that these effects may be easily overwhelmed by noise in the learning environment when investigating the actual L2 learning phenomena. Results of this study echo the inconsistent findings in previous L2 research on skewed input in construction learning (Lee, 2008; Nakamura, 2008a, 2008b; Year, 2009; Year & Gorden, 2009). Further research is also clearly needed in order to assess the durability of the effects of skewed input in actual learning conditions, since only short term effects are reported here and in other published studies. The research especially needs to specify how much skewness is sufficient to be effective and what are the characteristics of the right distribution to maximally facilitate acquisition.

Compared to the effects of token frequency and skewed input, structured input exhibited a positive effect on both the trained and new nouns of an artificial language. The study findings suggest that structured input aids not only lexical learning but also advances learners' understanding of the category and constructions.

Encountering pairs of grammatically and semantically related nouns in a contiguous manner is likely to make their paradigmatic relationships salient, providing the repeated opportunity for the learner to have correct semantic analysis and find the right combinations of their formal and semantic relations. Studies have only begun to investigate the issue of mode of input presentation experimentally for L2 learning, and thus these possibilities are open questions that must be examined in further empirical research. More research is needed to examine whether the positive effects of structured input found in this study can be validated in actual settings in L2 learning of noun classes and the constructions associated with them.

Although more empirical evidence needs to be accumulated, the positive effects of structured input found in the current study can be applicable to these L2 language classrooms. Structured input can be designed in such a way that learners encounter pairs of grammatically and semantically related nouns in a contiguous manner, providing the repeated opportunity to have correct semantic analysis and to find the right combinations of their formal and semantic relations. In this way, provision of structured input may help advancing learners' understanding of the noun class category and constructions. Careful consideration is needed when utilizing the input manipulations regarding the effects of structured input explored in the current study. The learning process described in this study was of a short-term nature and was only an initial stage of learning. It is important to investigate the durability of the positive effect of structured input in further research. Another important limitation of this study is that the factor of type frequency was not examined in this dissertation at all. Type frequency has been identified by some researchers as crucial for construction learning (Bybee 2010; Ellis, 2002). Therefore, it is equally important to investigate the potential effects of type frequency in relation to the effects of structured input on construction learning in future research, specifying what kind of knowledge learners may gain though exposure to the exemplars with high type frequency. However, in this study, it was necessary to hold the values of type frequency constant in order to manipulate token frequency, frequency distribution, and mode of presentation to investigate the research questions using a common vocabulary and training and testing sets.

Another future direction for research that would build on the findings of this study would be to explore the role of awareness or "noticing" in construction learning. One of the assumptions underline the study is that various manipulations of input work by focusing learner's attention on relevance correlations between linguistic form and meaning and the acquisition of new categories and constructions requires some level of awareness. For example, conscious registration of input stimuli, promoted by high token frequency, is assumed to be important in establishing strengthening memory traces for trained items. Establishment of new linguistics categories (such as the two noun class categories devised for this study) is assumed to require some higher level of awareness ("understanding" in Schmidt's terminology (1990)) of the underlying semantic basis of the categories. However, none of these assumptions were directly addressed in this study because careful investigation of the subjective mental experiences of study participants was incompatible with the on-line methodology employed here.

Also, from the current analysis, it is not possible to extrapolate to the more durable effects of structured input hoped for in actual language classrooms, because the findings of this research were derived from the learning of an artificial language in a short training session. A valuable future study might look for similar results using real language in real language classrooms with prolonged exposure.

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