

**The role of exposure condition on the cross-situational learning of vocabulary and morphosyntax: Linear mixed effects reveal local and global effects of acquisition**

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**Word count: 7827**

Acknowledgments: This work was supported by the International Centre for Language and Communicative Development (LuCiD) at Lancaster, funded by the Economic and Social Research Council (UK) [ES/L008955/1], and by the LEAD Graduate School and Research Network [DFG-GSC1028], a project of the Excellence Initiative of the German Federal and State Governments.

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## **Abstract**

First language acquisition is implicit, in that explicit information about the language structure to be learned is not provided to children. Instead, they must acquire both vocabulary and grammar incrementally, by generalizing across multiple situations that eventually enable links between words in utterances and referents in the environment to be established.

However, this raises a problem of how vocabulary can be acquired without first knowing the role of the word within the syntax of a sentence. It also raises practical issues about the extent to which different instructional conditions – about grammar in advance of learning or feedback about correct decisions during learning – might influence second language acquisition of implicitly experienced information about the language. In an artificial language learning study, we studied participants learning language implicitly, but under different instructional conditions. Language learners were exposed to complex utterances and complex scenes and had to determine the meaning and the grammar of the language from these co-occurrences with environmental scenes. We found that learning was boosted by explicit feedback, but not by explicit instruction about the grammar of the language, compared to an implicit learning condition. However, the effect of feedback was not general across all aspects of the language. Feedback improved vocabulary, but syntax learning was better without feedback. We further investigated the local, contextual effects on learning, and found that previous experience of vocabulary items improved learning but that this was moderated by instructional condition. The results have implications for theories of second language learning informed by our understanding of first language acquisition as well as practical implications for learning instruction and optimal, contingent adjustment of learners' environment during their learning.

## **Introduction**

The processes by which children acquire their first language have important implications for theories of second language acquisition. In order to understand an utterance, the language learner has to develop an understanding of both the meaning of words within the utterance through acquisition of the vocabulary, but at the same time determine the grammatical roles of those words from the syntactic structure of the sentence. Such an issue faces both first and second language learners, and has raised a long-standing theoretical debate about how these two interlinked aspects of language can be learned simultaneously (Gentner, 1982; Gleitman, 1990; Gleitman, Cassidy, Nappa, Papafragou, & Trueswell, 2005). Consider, for instance, the transitive verb “give”. Observing one person handing a gift to another accompanied by the sentence “Patrick gives the present to Simon”. Without already knowing the vocabulary for Patrick and Simon as well as the grammar that specifies word order in English would it be possible to ascertain from the scene whether “give” means giving or receiving. Only prior acquisition of vocabulary and grammar can result in accurate performance.

So how do learners resolve this “chicken and egg” problem of requiring vocabulary to understand grammar and requiring grammar to determine the meaning of the vocabulary? One solution is to focus the learner on acquiring one aspect of the language. For instance, many previous laboratory-based studies that train participants to acquire vocabulary and grammar typically expose learners to the vocabulary first, and then present this pre-acquired vocabulary in sentences to support development of the grammar (e.g., Friederici, Steinhauer, & Pfeifer, 2002). However, it is not known the extent to which this prior exposure is necessary, or even useful, for supporting language learning, and it seems to violate the situation that occurs in first language acquisition under naturalistic conditions.

In first language acquisition, infants tend to hear words spoken in multi-word utterances (Cameron-Faulkner, Lieven, & Tomasello, 2003), and are simultaneously

surrounded by a multitude of possible referents to which these words may relate. Children do not receive this explicit pre-training in vocabulary before they receive the vocabulary embedded in the utterance. Furthermore, they are not provided with information about the referent for each word. This has to be acquired implicitly. Indeed, determining how each of the words in the utterance refer to aspects of the environment is a profoundly difficult problem because the possible referents are unconstrained (Quine, 1960). For any individual word, there are infinite possible referents in the environment to which that word refers – so if a speaker of a native language utters “gavagai” when a rabbit runs past, the hearer cannot know if the utterance refers to the rabbit, the rabbit’s ear, its colour or texture, the action of running, a tasty meal, or the entire scene.

To quantify this ambiguity, Yu and Ballard (2007) analysed a small corpus of child-directed speech at the same time encoding which potential objects were around the child as each utterance was spoken. They found that multiple potential objects were present when the child heard each word, but over multiple occurrences of the word particular words tended to co-occur with particular objects that were within the child’s view at that moment (Siskind, 1996). Yu and Smith (2007) and Smith and Yu (2008) showed that adults and children could learn particular word-referent mappings from these cross-situational statistics. When sets of words and sets of objects co-occurred, it is not possible to determine which word refers to which object, but over multiple trials, as the words and objects vary, that certain words always occur when certain objects are in view becomes detectable by the learner.

This cross-situational learning proves to be a powerful mechanism for acquiring vocabulary from multiple words and multiple objects presented simultaneously. However, this experimental situation still does not reflect the complexity facing the learner of vocabulary and grammar in an unknown language. In these studies of cross-situational learning, the words were all nouns and their referents were always present. In naturalistic

language acquisition, words sometimes occur without any concrete referents. Yu and Ballard (2007), for instance, showed that verbs were also present in the multi-word utterances of parents speaking to infants, as well as function words which served a grammatical role but without any precise link to objects in the environment.

Monaghan and Mattock (2012) showed that language learners were able to cope with the added complexity of words occurring without referents for all words present in the environment. They presented learners with an artificial language comprising one word referring to one of two objects in the environment, one word that did not refer to anything in the environment. The referring and non-referring word varied in order across utterances, and participants were required to respond whether they felt the left or right object was referred to by the sentence. For a single trial, participants would not be able to determine which was the target object, but over multiple trials cross-situational statistics would give information about co-occurrences between individual words and objects. A condition where additional function words that indicated which was the referring word was also tested. Participants were able to learn the meaning of the referring words, and learning was boosted by the condition where additional function words were present (see also Koehne & Crocker, 2015). Thus, even though participants were not explicitly told about the language, they were able to use the grammatical information to support their acquisition of the vocabulary.

Studies of cross-situational word learning for verbs, similar in design to those by Yu and Smith (2007), have shown that learners can acquire word-action mappings in a similar manner to acquisition of nouns (Childers, Heard, Ring, Pai, & Sallquist, 2012; Scott & Fisher, 2012). Monaghan et al. (2015) further showed that learners can cope with further complexity of referring words from multiple grammatical categories being present in the language. They presented participants with intransitive sentences in an artificial language comprising a noun and a verb, and presented participants with two scenes of a shape object

performing a movement. Participants had to decide whether the left or the right scene corresponded to the sentence. The shape object and the action of one of the scenes were the target referents for the noun-verb utterance, and over multiple trials participants could learn again the co-occurrence between particular nouns and objects and verbs and actions, if they were able to identify that two grammatical categories occurred in the utterance and referred to different aspects of the scene. Monaghan et al. (2015) found that both the nouns and the verbs could be learned from these cross-situational statistics, without participants needing prior information about the grammar of the language.

In each of these previous studies of cross-situational learning, the focus had been on vocabulary acquisition, with simple grammatical structures tested for the extent to which they can support vocabulary acquisition. But none of these studies tested or questioned participants about what aspects of the grammar were acquired at the same time as the vocabulary – they provide only accumulating evidence that the grammar could be used to support vocabulary learning. Nonetheless, these studies of cross-situational learning demonstrate that vocabulary can be acquired from utterances that comprise more than lists of words from the same grammatical category, so it is not necessary for vocabulary to be acquired prior to words occurring in multi-word utterances.

However, the utterances so far tested are extremely simple (comprising only intransitive sentences), and as such do not address the complexity of natural language grammar, where utterances may be substantially longer and be composed of words from several grammatical categories. The use of only intransitive sentences also does not address the ambiguity that can come from resolving subjects and objects of verbs, as in the give/receive example.

Rebuschat et al. (submitted) recently extended the cross-situational paradigm to a more complex design using a language with transitive sentences comprising nouns, verbs,

adjectives, and grammatical role words that indicate the subject and object of the sentence. The grammar was based on Japanese, with word order either SOV or OSV, with the grammatical role word occurring after the subject or object noun to indicate its role. As well as the grammar being more complicated, the scenes viewed by participants were also more complex, involving two aliens (referred to by the nouns in the language) with different colours (referred to by the adjectives in the language) undertaking an action (described by the verb). As with the other studies of cross-situational learning, two scenes appeared, and participants had to select which scene was described by the utterance. If participants were able to track the cross-situational statistics between each word in the utterance and objects and their roles and colours, and the action that the objects performed, then learners should be able to select the target scene with increasing accuracy. This was found to be the case. Despite the complexity of the language and the scene, learning was successful: vocabulary in each grammatical category was acquired greater than chance.

Rebuschat et al. (submitted) also tested whether participants could learn the grammar of the language, by testing ability to recognize grammatical versus ungrammatical word sequences. They found that this was also successful. Thus, the chicken and egg problem of acquisition of vocabulary and of grammar was shown to be resolved through cross-situational statistics, with learners tracking multiple possible mappings between words and aspects of complex scenes in order to hone in on the co-occurring features of the environment and words that labeled these features.

### **Effects of Feedback and Explicit Information on Language Learning**

These previous studies of cross-situational learning demonstrate that learners are adept at detecting complex co-occurrences between words in utterances and multiple features of scenes. Furthermore, these studies show that feedback on whether or not the learner is

making correct assumptions is not necessary for acquisition. In all these studies, learning is presented entirely implicitly, with no feedback given on responses. This shows the power of language learning – that it can proceed in the absence of feedback – but what is not known is whether feedback can promote language learning under these cross-situational learning conditions that the first language learner finds her or himself. Certainly, infants acquiring their first language receive substantial feedback (implicit and explicit) on their attempts to communicate and use words referentially (Baldwin, 1993; Miller & Lossia, 2013; Tamis-LeMonda, Kuchirko, & Song, 2014).

In second language learning, feedback is also known to provide a boost to learning (N. Ellis, 1990; Goo et al., 2015; Lightbown & Spada, 1990; Li, 2010; Loewen, 2012; Mackey, 2006; Nassaji, 2016; Nakata, 2015). For instance, meta-analytic work has reported a significant effect size for feedback on learning, especially for more explicit types of feedback (Goo et al., 2015, see also Li, 2010). Feedback helps learners notice the gap between their representation of the second language and that of the target (Nassaji, 2016). Feedback can also assist learners in acquiring difficult target forms, including rare, non-salient, or semantically redundant forms (Loewen, 2012). But how does feedback affect cross-situational learning of language? There are two theories of how language learners acquire word-referent mappings from cross-situational statistics (MacDonald, Yurovsky, & Frank, 2017; Yurovsky, Smith, & Yu, 2013), each of which would have different mechanisms for feedback to affect learning. The first theory (propose-but-verify, Trueswell, Medina, Hafri, & Gleitman, 2013) contends that language learners generate a hypothesis about a word-referent mapping, then search for confirmatory evidence of the link. If the proposed word-referent mapping is not correct, then the information in future learning situations to verify this will be weak, and the proposed mapping will be set aside by the learner. The alternative theory (McMurray, Horst, & Samuelson, 2012) is that participants do not make explicit proposals



about mappings, but instead gradually acquire associations between particular words and referents in the environment. Co-occurring words and referents become incrementally strengthened as a consequence of exposure, until the actual word-referent mappings eventually have the strongest links in the learner's representation of the vocabulary. Feedback about what is correct will have a different effect on learning according to each theory, but potentially with the same observable effect on learning. In the case of propose-but-verify, explicit feedback enables the verification to be instantaneous – if the proposal of the word-referent mapping is erroneous or correct then sufficient information is provided in feedback for this proposal to be dropped. On the other hand, for the associative learning theory of cross-situational vocabulary learning, feedback could provide an additional boost to the associative strength between the word and the referent if the association is receptive to external information about correct mappings. If this is the case, learning of the mapping would be faster, though this would still be slow in comparison to the immediate learning under the propose-but-verify theory. Under both theories, then, feedback can support learning of implicit cross-situational information.

However, until now, the role of explicit feedback about correct selection of referents in cross-situational learning tasks has not been comprehensively tested. In this study we tested the extent to which feedback about correct scene selections supported learning. Theoretically, this is important to know how such external information about learning inter-relates with acquisition of implicit statistical information about vocabulary and grammar. Practically, it is also vital to determine what manipulations of the learning environment support language learning, and whether these affect in particular vocabulary or grammar, or apply equally to both.

The cross-situational learning studies, such as Rebuschat et al. (submitted), have shown that learning vocabulary and grammar is possible simultaneously, and without explicit

instruction about either vocabulary or grammar. However, there is a wealth of data showing that explicit information about the language to be learned supports learning (R. Ellis, 2005, 2015; N. Ellis, 2005; Goo et al., 2015; Norris & Ortega, 2000; Spada & Tomita, 2010). Yet, how precisely this explicit information about language structure impacts on language representation in second language acquisition is not fully understood. It could, for instance, affect the participants' understanding of the grammatical structure, which then facilitates accumulation of vocabulary (thus, solving the chicken-and-egg problem of grammar and vocabulary learning), or it could be that it only improves grammar learning and vocabulary acquisition proceeds largely independently of this grammatical knowledge. Monaghan, Schoetensack and Rebuschat (2019) made some progress in addressing this question of how explicit information about language structure affects language learning. Using a paradigm similar to Monaghan et al. (2015), where utterances comprised a noun and a verb, in free word order, with function words indicating the grammatical categories preceding the function word, participants were instructed about the role of the function words, or were left to acquire the language cross-situationally with no information about the grammar. Participants were able to learn the meaning of the nouns and the verbs more effectively in the condition with explicit grammar instruction.

However, this study only tested acquisition of vocabulary, and was limited in the range of grammatical categories included in the language. As N. Ellis (2015) notes more broadly, "The central issue of the Interface Question is just how much do explicit learning and explicit instruction influence implicit learning, and how can their symbiosis be optimized?" (p. 36). In order to enrich our understanding of the points at which explicit information impacts on otherwise implicit acquisition of language from cross-situational statistics, we require a test of how explicit information about the grammar can affect both grammatical knowledge and vocabulary knowledge, preferably of vocabulary present in a

variety of grammatical categories, including both content and function words, the latter of which have a grammatical role in the language, and tend to be accompanied by less explicit information about their meaning (Paradis, 2009) and less explicit control over their usage (Groom & Pennebaker, 2002).

A second aim of the current study was thus to test the role of explicit instruction about the grammatical structure of a more complex artificial language, taken from Rebuschat et al. (submitted), involving tests of grammatical structure as well as different vocabulary types. We therefore compared groups that were given explicit information about the grammatical structure to groups that were given no such information and had to derive this knowledge from the information provided during (implicit) learning.

A further advance in determining how and where explicit and implicit information can impact on vocabulary and grammar learning is to investigate the very local learning context effects applying during acquisition. Classic statistical approaches to behavioural studies (e.g., N. Ellis, 2006; Monaghan & Mattock, 2012; Nassaji, 2016; Yu & Smith, 2007) examine summary statistics in order to determine whether there are differences between one group of responses and another group of responses (e.g., for implicit or explicit conditions in a learning study). These statistical approaches measure the global effects of learning. However, they fail to take into account the specific situation that learners experience from one learning trial to the next. Classic statistics can show that explicit instruction improves vocabulary acquisition, but to what extent does the learner's previous exposure to a linguistic structure affect their learning of this structure the next time they come across it? Using modern statistical techniques – specifically, linear mixed effects modelling approaches (Baayen et al., 2008) – enables studies of language learning to investigate the contingency of learning based on previous performance as learning proceeds (Cunnings, 2012; Linck & Cunnings, 2015).

In the analyses we undertake in this paper, to investigate the role of feedback and the consequences of implicit and explicit instruction, we use these linear mixed effects methods to hone in on precisely how learning proceeds trial by trial. We investigate how performance on the current learning trial is affected by whether participants made a correct or incorrect response on a previous trial containing the same information in terms of the nouns, verbs, and adjectives that appeared. This enables us to test whether instruction and feedback affects the way in which this previous information is used in the current trial, and how learning transfers across different grammatical categories. It could be that knowledge of a particular noun is influenced by whether the noun was correctly interpreted in the previous trial. It could also be the case that knowledge of the verb in a particular trial influences knowledge of the noun that the verb now appears with. This local information enables us to determine how learning from one source of information scaffolds learning across the language as a whole.

We next report the experimental study varying feedback and instruction conditions in learning a complex artificial language from cross-situational statistics. We predict that feedback about performance will improve learning of both vocabulary and grammar as training proceeds. We also predict that explicit information about the language structure will have a direct influence on representation of the grammatical information, but also will have indirect influence on acquisition of vocabulary within this grammar. Finally, we perform explorative analyses to determine where these different conditions of learning (feedback, implicit or explicit instruction) affect the way in which information transfers between language structures within the language by analyzing performance at the item by item level, considering how global learning conditions affect local learning.

## **Method**

### **Participants**

Ninety university students (Mean age = 22.1, SD = 3.3, 57 women) volunteered to participate. All participants were native speakers of English, and none had a background in Japanese. Participants were remunerated for their time. The study was approved by the ethics review panel of the Faculty of Arts and Social Sciences at Lancaster University and conducted in accordance with the provisions of the World Medical Association Declaration of Helsinki. Data collection took place in Lancaster, UK, and in Tübingen, Germany.

### **Materials**

The materials were closely based on the study of Rebuschat et al. (submitted). Eight alien cartoon characters served as referents to nouns in the artificial language (see Supplementary Materials for images). The aliens appeared in either red or blue and were depicted performing one of four actions (hiding, jumping, lifting, pushing) in animated scenes generated by E-Prime 2.0 (Schneider, Eschman, & Zuccolotto, 2002). Figure 1 shows a sample trial.

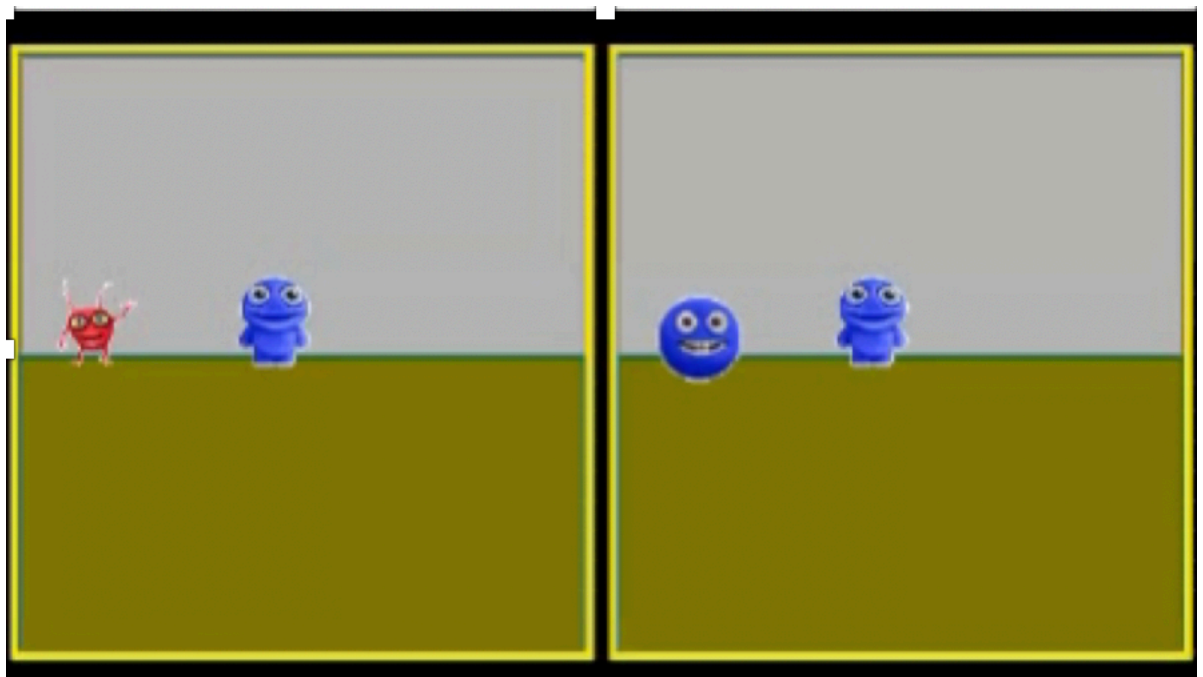


Figure 1. Still from a training trial. An agent and a patient appear in each scene, with varying colours (red or blue) performing an action. One of the scenes is referred to by the spoken sentence accompanying the trial.

The artificial language contained 16 pseudowords, taken from Monaghan and Mattock (2012) (see Supplementary Materials for list of stimuli). Fourteen bisyllabic pseudowords were content words: Eight nouns (one per alien), four verbs (one per action), and two adjectives (one per colour). Two monosyllabic pseudowords served as grammatical role markers and reliably indicated if the preceding noun referred to the subject or the object of the sentence. Word-referent mappings were randomly generated for each participant to control for preferences in associating certain sounds to objects, actions, or colours.

The grammar of the artificial language was verb final with variable word order, similar to the grammar of Japanese. Sentences could either be SOV or OSV, i.e. the verb (V) had to be placed in final position but the order of subject and object noun phrases (NP) was free. NPs contained an optional Adjective (A) pre-nominally, a noun (N), and a post-nominal grammatical role marker that indicated if the preceding noun was the subject (SUBJECT) or the object (OBJECT) of the action. Adjectives occurred in half the NPs. Sentence length thus ranged between five and seven words. We generated 192 unique sentences which were divided into four training blocks each of 48 sentences. Within each block lexical frequencies, subject or object assignment, and word order were balanced. Table 1 summarizes the grammatical sentence patterns that occurred, with equal frequency, in the experiment. A further 96 unique test sentences were also generated and were controlled in a similar way to the training sentences.

Table 1. Grammatical sentence patterns that occurred in the experiment.

Word order	Sequence		
	First	Second	Third
SOV	NP <sub>subj</sub> (A N SUBJECT)	NP <sub>obj</sub> (A N OBJECT)	V
	NP <sub>subj</sub> (A N SUBJECT)	NP <sub>obj</sub> (N OBJECT)	V
	NP <sub>subj</sub> (N SUBJECT)	NP <sub>obj</sub> (A N OBJECT)	V
	NP <sub>subj</sub> (N SUBJECT)	NP <sub>obj</sub> (N OBJECT)	V
OSV	NP <sub>obj</sub> (A N OBJECT)	NP <sub>subj</sub> (A N SUBJECT)	V
	NP <sub>obj</sub> (A N OBJECT)	NP <sub>subj</sub> (N SUBJECT)	V
	NP <sub>obj</sub> (N OBJECT)	NP <sub>subj</sub> (A N SUBJECT)	V
	NP <sub>obj</sub> (N OBJECT)	NP <sub>subj</sub> (N SUBJECT)	V

## Procedure

Participants were randomly distributed into one of three conditions, implicit ( $n = 30$ ), explicit ( $n = 31$ ), and feedback ( $n = 29$ ). After providing informed consent, participants in all conditions were informed that they would learn a new language, spoken by the “friendly inhabitants of a distant planet”.

Participants in all three conditions first completed two practice trials with two scenes involving aliens performing actions, accompanied by a sequence that followed the grammar of the language (so containing the grammatical role words) but did not contain any of the nouns, adjectives, or verbs from the main part of the study. The aliens, their colours (green), and the actions used in the practice also did not occur in the main part of the study.

Before these practice trials, participants in the explicit condition were given information about the grammatical role words, as follows: “In the sentence, there are two marker words that tell you who is the subject (= the person who does something) and who is the object (= the person to whom something happens). These marker words are ‘tha’ and ‘noo’.” Participants in

the implicit, and feedback conditions received no such instructions as to the structure of the language.

Participants in all conditions were then trained and tested on the artificial language over twelve blocks of training, with testing blocks occurring after every six training blocks.

**Training blocks.** Participants then viewed the animated scene in which two alien characters performed an action. They then heard the sentence describing the scene, e.g., for referring to the target scene shown on the left panel of Figure 1:

hagal chilad tha garshal sumbad noo thislin

blue alien<sub>2</sub> OBJECT red alien<sub>1</sub> SUBJECT jumps

*gloss:* “red alien<sub>1</sub> jumps blue alien<sub>2</sub>”

This was then followed by another presentation of the action. Participants were required to make a response to either the left or the right scene as being referred to by the sentence, by pressing a button on a computer keyboard. In the feedback condition, an auditory bell sound was played if the participant responded correctly. In the other conditions, no feedback was given. There were 16 trials in a training block, with each alien, action, and colour, and each word occurring a balanced number of times within each block.

**Test blocks.** The testing procedure was the same for all conditions, except that in the feedback condition, as in the training blocks, participants were given auditory feedback as to whether their response was correct or not. The acquisition of vocabulary was assessed in a test block after every training block, by means of a two-alternative forced-choice task. Participants were presented with two animated scenes and played a test sentence. Their task was to decide as quickly and accurately as possible which the scene the sentence referred to. Each lexical category was assessed by varying the target and distractor scenes by one piece of information, such that knowledge of the vocabulary relating to the individual piece of information was required to determine which scene was described by the utterance. Thus, to test noun learning,



participants saw two scenes that only differed with regards to one alien character. In the verb test trials, only the actions were different between the scenes. In the adjective test trials, the colours of the aliens were switched. Finally, in the grammatical role marker test trials, the subject/object assignment was reversed, though note that understanding the grammatical role markers could be considered part of the grammar rather than the vocabulary.

Each vocabulary test block consisted of 24 trials, of which sixteen trials were used for testing lexical knowledge, four for each grammatical category, with a further eight trials used as fillers, in which the distractor scene was randomly assigned and so could vary by several aspects. Trials occurred in randomised order. An example test trial for a verb test is shown in Figure 2.

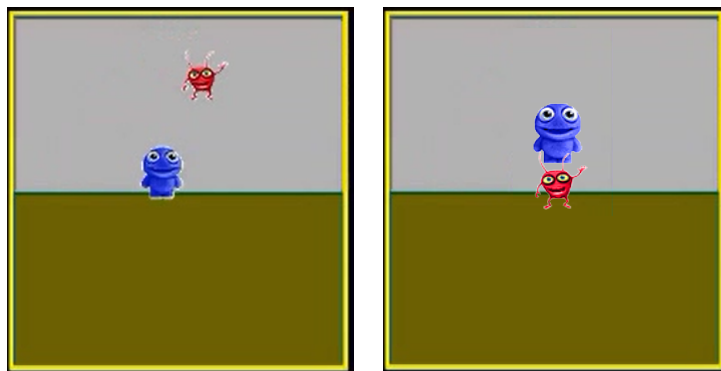


Figure 2. Example of a still from a vocabulary test trial, measuring knowledge of the verb (aliens, colours, and subject/object roles are the same in both scenes).

After the vocabulary testing, acquisition of grammar was then tested by a grammaticality judgment task where word order was varied between grammatical and ungrammatical sequences. Participants were told that they would see a scene and hear a sentence spoken by another alien from a very different planet who was also learning the new language. Their task was to decide, as quickly and accurately as possible, whether the new alien was speaking

correctly. If the sentence sounded “good”, participants had to press a green button on a computer keyboard. If it sounded “funny”, they had to press a red button. Feedback was provided on response accuracy only for participants in the feedback condition. Half the trials followed the grammar of the artificial language, with SOV and OSV sentence patterns carefully counterbalanced. The other half involved sentences with syntactic violations (\*SVO, \*OVS, \*VSO, \*VOS). Presentation order within each block was randomised.

After the final test block, participants completed a debriefing and language background questionnaire.

### **Statistical analyses**

The use of mixed-effects regression modelling is increasingly advocated as a tool to analyse second language data (e.g., Cunnings, 2012; Cunnings & Finlayson, 2015; Linck & Cunnings, 2015; Murakami, 2016; Plonsky, 2017; Plonsky & Oswald, 2017), since it allows to account for the effects of multiple factors on the dependent variable as well as accounting for individual variation between different participants and stimuli in the same study (Linck, 2016). Hence, experimental condition effects and inter-individual differences can be estimated within a single analysis.

In the present study, mixed-effects regression models were used to assess both global and local effects of acquisition, i.e., the effects of the different exposure conditions (feedback, explicit, and implicit) and the effects of the more immediate context in which a stimulus is processed, respectively. To this end, the lme4 package (version 1.1-21; Bates et al., 2015) of R (version 3.6.0; R Core Team, 2019) was used. For the analysis of adjectives, nouns, verbs, and morphology in both training and testing data, logistic mixed-effects regression models (Jaeger, 2008) were constructed. For the analysis of word order syntax in the testing data, however, a linear mixed-effects model (Baayen, Davidson, & Bates, 2008) was built to model the data from the grammaticality judgement task, given that the raw

accuracy scores obtained from this task were transformed into d-prime ( $d'$ ) scores (Wickens, 2002) to reduce response bias. Thus, in the linear mixed-effects model the dependent variable was the d-prime value. In the logistic mixed-effects models, on the other hand, accuracy was modelled as a binary dependent variable (correct = 1, incorrect = 0).

To test global effects on learning, Group (Feedback vs. Explicit vs. Implicit) and Block were entered as fixed effects, and Subjects and Items were entered as random crossed effects (Baayen et al., 2008). Furthermore, in order to determine the effect of Group on the different type of tests in the testing trials, the variable Test (Adjective vs. Marker word vs. Noun vs. Verb) was used as a fixed effect. The categorical variables Group and Test were contrast-coded (see Tables 2, 3, and 6) (Cohen et al. 2003).

To determine the influence of local context on learning, i.e., whether the accuracy for the previous trial in which the nouns, adjectives, and verbs occurred affected accuracy of the current trial, the participants' response (correct/incorrect) in the previous occasion this particular aspect of the language occurred was included as an additional fixed effect in the models used for the analysis of training data (encoded for each type of word as previous noun, previous verb, and previous adjective). For the local context analysis of testing stimuli, however, only the accuracy on the previous noun and the previous verb were included as fixed effects in the models because there were not sufficient testing trials to isolate effects of the previous adjective performance.

## **Results**

### **Performance across training blocks**

The performance during the training task is summarized in Figure 3 and Table 1.

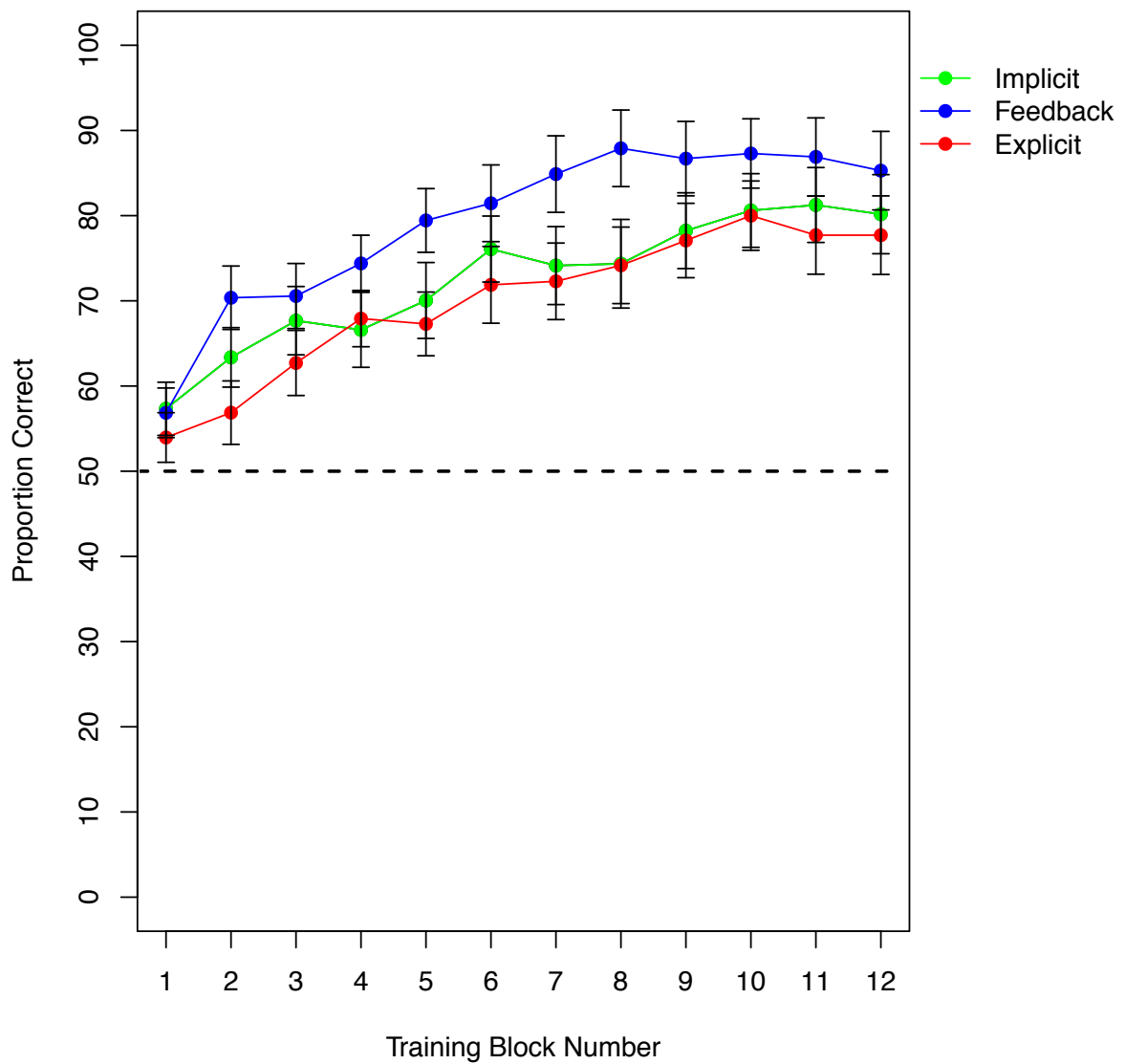


Figure 3. Performance for training blocks. Error bars show standard error of the mean. Dotted line at 50 shows chance performance.

Table 1. Descriptive statistics for training blocks.

Groups	Training Block											
	1	2	3	4	5	6	7	8	9	10	11	12
Implicit <sup>a</sup>												
<i>M</i>	57.33	63.36	67.67	66.59	70.04	76.08	74.14	74.35	78.23	80.60	81.25	80.17

<i>SD</i>	16.79	18.80	21.59	23.70	24.00	20.87	24.65	28.02	23.95	23.29	23.68	25.00
<i>SE</i>	3.12	3.49	4.01	4.40	4.46	3.88	4.58	5.20	4.45	4.32	4.40	4.64
Feedback <sup>b</sup>												
<i>M</i>	56.85	70.36	70.56	74.40	79.44	81.45	84.88	87.90	86.69	87.30	86.90	85.28
<i>SD</i>	12.95	22.07	20.17	22.90	19.51	22.33	19.82	18.39	20.20	21.50	19.59	19.80
<i>SE</i>	2.33	3.96	3.62	4.11	3.50	4.01	3.56	3.30	3.63	3.86	3.52	3.56
Explicit <sup>c</sup>												
<i>M</i>	53.96	56.88	62.71	67.92	67.29	71.88	72.29	74.17	77.08	80.00	77.71	77.71
<i>SD</i>	15.95	20.39	20.92	18.11	20.48	24.66	24.60	24.61	23.92	22.29	25.09	25.25
<i>SE</i>	2.91	3.72	3.82	3.31	3.74	4.50	4.49	4.49	4.37	4.07	4.58	4.61

<sup>a</sup> *n* = 29. <sup>b</sup> *n* = 31. <sup>c</sup> *n* = 30.

In terms of global properties of learning, a mixed-effects logistic model was constructed to determine the interaction of group and block on the training performance. There was a significant effect of Block, indicating that participants improved in performance with additional training. There was no significant effect of group overall, but there was a significant interaction between group and block,  $\chi^2(2) = 17.05, p < .001$ , indicating that rate of learning over the blocks differed between the groups. To clarify this effect, further mixed-effects models using contrast coding (Cohen et al., 2003) were fitted. Results showed that there was an average linear increase of performance across the training blocks (estimate = 0.15,  $SE = 0.01, p < .001$ ), with a much more pronounced linear effect (i.e., steeper slope, faster learning) in the Feedback condition (estimate = 0.02,  $SE = 0.004, p < .001$ ) than the linear component in the Implicit and Explicit conditions combined (i.e., average over these two groups), which did not differ significantly (estimate = 0.003,  $SE = 0.01, p = .697$ ) (see Table 2).

*Table 2. Logistic mixed-effects regression for global effects of learning in training blocks*

Fixed effect	Estimate	<i>SE</i>	<i>p</i>
Intercept	0.442	0.130	.001
CG1	0.072	0.087	.409
CG2	-0.099	0.153	.518
Block	0.146	0.008	< .001
CG1:Block	0.018	0.004	< .001
CG2:Block	0.003	0.007	.697
Random effects	Variance	<i>SD</i>	
Items	0.061	0.247	
Subjects	1.243	1.115	

*Note.* Group was contrast coded, as follows: CG1(Feedback = 2, Explicit = -1, Implicit = -1; CG2 (Feedback = 0, Explicit = 1, Implicit = -1).

In terms of the local properties of learning, a mixed-effect logistic model was used to test the effect of local context on learning in the training blocks, i.e., estimating how much likely it is to predict the correctness of the current trial based on the correctness of the previous noun, verb, or adjective, regardless of what type of word the current item is. There was a significant interaction between word types and group, meaning that the local effects varied as a consequence of instruction,  $\chi^2(10) = 22.28$ ,  $p = 0.014$ . In particular, it made a difference for the verbs, but not for the other word types. As shown in Table 3, in the Feedback condition, the prediction from the verbs is smaller than in the Explicit and the Implicit conditions combined (estimate = 0.06,  $SE = 0.03$ ,  $p = .067$ ), and the Explicit and the Implicit groups also differ (estimate = -0.18,  $SE = 0.05$ ,  $p = .001$ ). Particularly, in the Implicit group the prediction from the previous verb was the highest (estimate = 0.672,  $SE = 0.08$ ,  $p < .001$ ), followed by the Feedback group (estimate = 0.307,  $SE = 0.08$ ,  $p = .001$ ), and the Explicit group, with the lowest prediction (estimate = 0.305,  $SE = 0.07$ ,  $p < .001$ ). Table 3 also reports the average prediction for the other word types across the three groups, i.e., nouns in subject (estimate = 0.15,  $SE = 0.04$ ,  $p = .001$ ) and object (estimate = 0.13,  $SE = 0.04$ ,  $p = .003$ ) position; and adjectives in either subject (estimate = 0.11,  $SE = 0.05$ ,  $p = .031$ ) or object (estimate = 0.18,  $SE = 0.05$ ,  $p = .001$ ) position.

Table 3. Logistic mixed-effects regression for local effects of learning in training blocks

Fixed effect	Estimate	SE	<i>p</i>
Intercept	-0.173	0.124	.163
CG1	0.142	0.082	.086
CG2	0.071	0.140	.612
Previous subject noun	0.147	0.044	.001
Previous object noun	0.135	0.045	.003
Previous verb	0.428	0.045	< .001
Previous subject adjective	0.112	0.052	.031
Previous object adjective	0.181	0.052	.001
Block	0.127	0.008	< .001
CG1:Previous subject noun	0.037	0.032	.256
CG1:Previous object noun	0.002	0.033	.952
CG1:Previous verb	-0.060	0.033	.067
CG1:Previous subject adjective	0.070	0.038	.066
CG1:Previous object adjective	-0.039	0.038	.303
CG2:Previous subject noun	0.007	0.051	.893
CG2:Previous object noun	-0.054	0.052	.294
CG2:Previous verb	-0.183	0.052	.001
CG2:Previous subject adjective	0.067	0.060	.270
CG2:Previous object adjective	-0.046	0.060	.443
Random effects	Variance	SD	
Items	0.063	0.251	
Subjects	0.900	0.949	

*Note.* Group was contrast coded, as follows: CG1(Feedback = 2, Explicit = -1, Implicit = -1; CG2 (Feedback = 0, Explicit = 1, Implicit = -1).

### Performance across test blocks

Accuracy for acquisition of nouns, verbs, adjectives, marker words, and syntactic word order for each of the four test blocks are shown in Figure 2, and Tables 4 and 5.

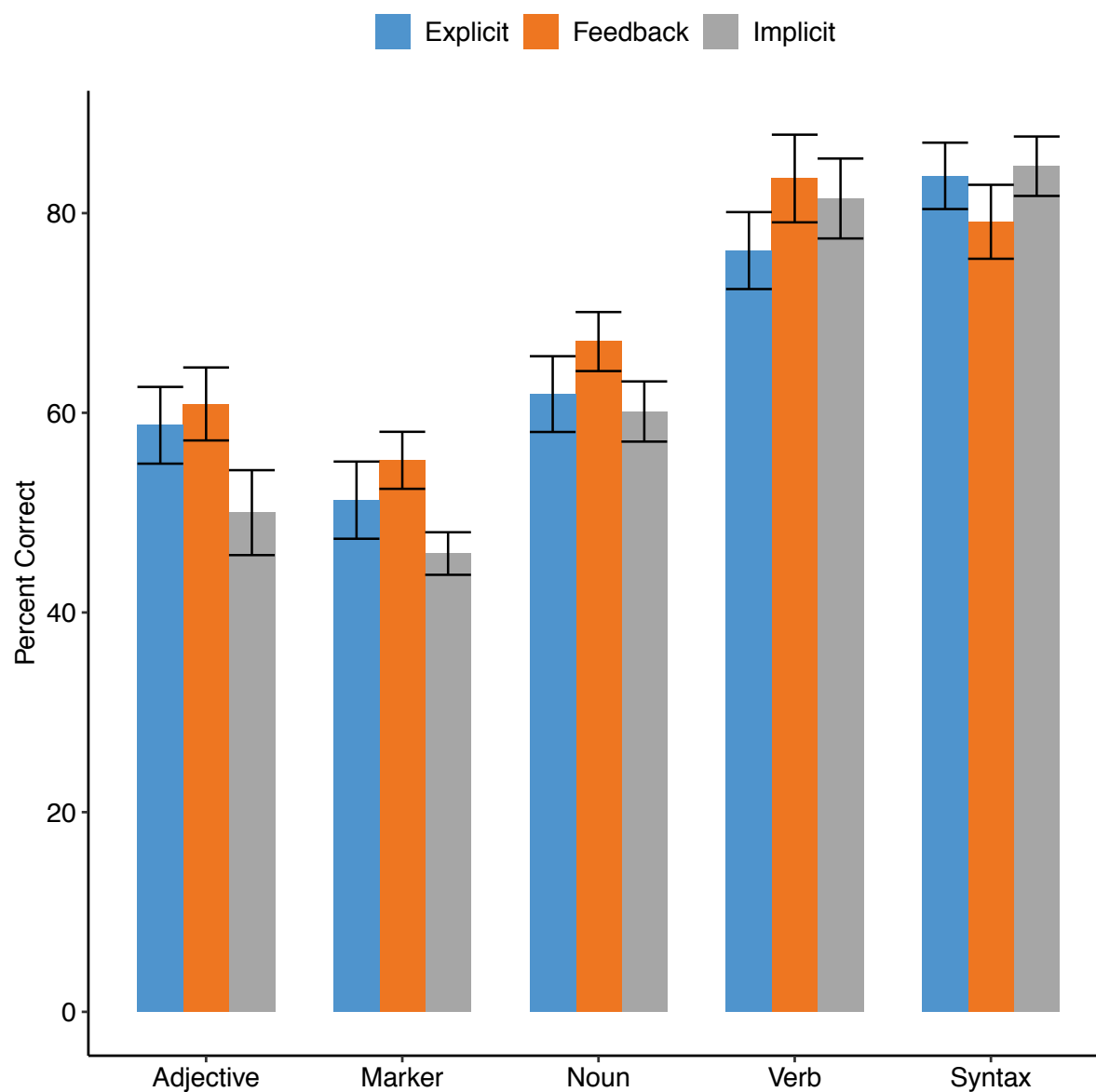


Figure 2. Performance for testing blocks. Error bars show standard error of the mean.

Table 4. Descriptive statistics for performance on adjective, marker word, noun and verb tests

Test		Implicit <sup>a</sup>	Feedback <sup>b</sup>	Explicit <sup>c</sup>
Adjectives	<i>M</i>	50.00	60.89	58.75
	<i>SD</i>	22.90	20.35	21.06



	<i>SE</i>	4.25	3.65	3.84
Marker words	<i>M</i>	45.91	55.24	51.25
	<i>SD</i>	11.49	15.90	21.17
	<i>SE</i>	2.13	2.86	3.87
Nouns	<i>M</i>	60.13	67.14	61.88
	<i>SD</i>	16.23	16.45	20.78
	<i>SE</i>	3.01	2.96	3.79
Verbs	<i>M</i>	81.47	83.47	76.25
	<i>SD</i>	21.55	24.45	21.11
	<i>SE</i>	4.00	4.39	3.85

<sup>a</sup> n = 29. <sup>b</sup> n = 31. <sup>c</sup> n = 30.

*Table 5. Descriptive statistics for performance on word order tests*

Test	Implicit <sup>a</sup>		Feedback <sup>b</sup>		Explicit <sup>c</sup>	
Word Order Syntax	<i>d'</i>		<i>d'</i>		<i>d'</i>	
<i>M</i>	84.70	2.44	79.13	2.05	83.72	2.41
<i>SD</i>	16.03	1.30	20.62	1.55	18.21	1.41
<i>SE</i>	2.98	0.24	3.70	0.28	3.32	0.26

<sup>a</sup> n = 29. <sup>b</sup> n = 31. <sup>c</sup> n = 30.

In order to test global effects (i.e., group differences) on the learning of adjectives, nouns, verbs, and morphology, a mixed-effect logistic model was applied to the testing data. A likelihood ratio test indicated that there was no interaction between test type and group,  $\chi^2(6) = 2.97, p = .813$ , meaning that the patterns of results across measures was similar between the groups. There is a tendency of the Feedback group to have higher scores across all

measures than the Explicit and the Implicit groups (CG1; estimate = 0.107,  $SE = 0.057$ ,  $p = .060$ ), whereas the Explicit and the Implicit groups are not different (CG2; estimate = 0.045,  $SE = 0.099$ ,  $p = .650$ ) (see Table 6).

In the case of word order syntax, the results of a likelihood ratio test indicated that there was a significant difference in overall performance between the groups,  $\chi^2(2) = 23.32$ ,  $p < .001$ . Further analysis revealed that the Feedback group scored significantly lower than the Explicit and the Implicit groups (estimate = -0.125,  $SE = 0.018$ ,  $p < .001$ ), whereas the Explicit and the Implicit groups did not differ in performance (estimate = -0.014,  $SE = 0.032$ ,  $p = .676$ ).

Regarding the effect of local context on testing data, neither correctness on the previous noun (estimate = 0.150,  $SE = 0.123$ ,  $p = .225$ ), nor the previous verb (estimate = 0.213,  $SE = 0.269$ ,  $p = .428$ ) affected current performance. This could have been due to the small number of items in the test phase, with local context effects on testing less evident than those observed during training.

*Table 6. Logistic mixed-effects regression for adjective, marker word, noun and verb tests*

Fixed effect	Estimate	$SE$	$p$
Intercept	0.725	0.084	< .001
CT1	-0.144	0.028	< .001
CT2	-0.416	0.044	< .001
CT3	-0.685	0.102	< .001
CG1	0.107	0.057	.060
CG2	0.045	0.099	.650
CT1:CG1	-0.004	0.019	.820
CT1:CG2	0.050	0.033	.130
CT2:CG1	-0.009	0.029	.747

CT2:CG2	0.060	0.050	.233
CT3:CG1	-0.024	0.065	.707
CT3:CG2	0.121	0.110	.272

Random effects	Variance	<i>SD</i>
Subjects	0.435	0.659
CT1	0.018	0.135
CT2	0.076	0.276
CT3	0.350	0.592

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*Note.* Group was contrast coded, as follows: CG1(Feedback = 2, Explicit = -1, Implicit = -1; CG2 (Feedback = 0, Explicit = 1, Implicit = -1).

Test was contrast coded, as follows: CT1 (Adjective = 3, Marker word = -1, Noun = -1, Verb = -1); CT2 (Adjective = 0, Marker word = 2, Noun = -1, Verb = -1); CT3 (Adjective = 0, Marker word = 0, Noun = 1, Verb = -1).

## **Discussion**

First language acquisition proceeds with little explicit information about the language to be learned – either in vocabulary or in grammatical structure – and few opportunities in receiving direct, explicit feedback about decisions about the referents for words within an utterance. In this study, we trained participants to acquire a complex, artificial language from co-occurrences between utterances and scenes containing objects, properties of objects, actions, and a distinction between subject and object roles of those objects. We replicated previous studies demonstrating that participants can resolve this difficult task (Rebuschat et al., submitted); learning the meaning of nouns, adjectives, verbs, and grammatical role function words by tracking cross-situational statistics between words and varying properties of the scenes that they viewed. Furthermore, participants could

also acquire the grammatical structure of the language – they showed learning of the syntax in terms of sensitivity to word order regularities of words in the speech.

The power of participants' learning shows that the conditions under which children acquire language – where both vocabulary and grammar are uncertain – is not an impossible impediment to language acquisition, and additional informational cues or structural biases within the learner are not necessary for learning to proceed (Baldwin, 1993; Gleitman, 1990; Gleitman et al, 2005; Smith & Yu, 2008; Yurovsky et al., 2013). Indeed, learning is extremely rapid under these conditions: after just a few dozen exposures to varying utterances appearing with scenes to which they refer, participants are better than chance at knowing the meaning of the words and identifying the syntax within those utterances. Hence, the chicken-and-egg problem of vocabulary and grammar acquisition is solvable as a consequence of sensitivity to cross-situational statistics (see also Abend, Kwiatkowski, Smith, Goldwater, & Steedman, 2017, for a computational demonstration of this ability).

Though the non-instructed condition demonstrates that this complex artificial language can be acquired implicitly, with no explicit instruction or feedback, we predicted that both feedback and explicit information about the language structure ought to support learners further in developing understanding of the language. This expectation was confirmed by the results.

In terms of feedback, we found that informing participants about whether they had selected the correct scene improved learning during training: there was a steeper trajectory of learning in the feedback condition than the explicit and implicit learning conditions, consistent with previous studies of the benefit of feedback on second language learning (Lightbown & Spada, 1990; Nakata, 2015; Nassaji, 2016). This benefit of feedback for learning also influenced performance during testing – for vocabulary

learning, participants in the feedback condition scored marginally higher overall than participants in the other conditions.

In terms of explicit instruction, we found no improvement in learning or testing performance as compared to the implicit condition. This was surprising, given that explicit instruction about grammatical structure tends to improve performance compared to conditions where no advance information about the grammar is provided (Goo et al., 2015; Norris & Ortega, 2000; Spada & Tomita, 2010). This may be a consequence of the implicit nature of the task (Rebuschat & Williams, 2012), where explicit knowledge of language structure emerges only gradually during learning (Monaghan et al., 2019). Participants had to learn associations between individual words in an utterance with relatively free word order, and different semantic features of a complex scene depicting a transitive action. Information about the general grammatical structure could help somewhat in determining the syntax of the language (which, as we discuss below, elicits an improvement in detecting that structure) but this does not seem to transfer to supporting learning of the precise associations between words and features of the scene.

This highlights a clear advantage of the laboratory-based language learning paradigm over more formal classroom-based language learning studies, because it enables us to hone in on precisely how learning proceeds, and where instruction and feedback exert their influence. This has not only practical implications for supporting language learners' progress in acquiring languages, but also theoretical insight into what aspects of learning are promoted by instruction and feedback. We can for instance ask whether this is focused on direct improvement of the grammatical structure, which is given by the explicit instruction, or whether this benefit spreads also to vocabulary (and if so, whether this applies to words within only some grammatical categories). In short, we were able to determine, for this language learning task, which regions of the implicit-explicit interface

(N. Ellis, 2015) are penetrated by feedback and by instruction about syntax.

We found that, for the testing trials, there was no significant interaction between vocabulary learning of word type and the effect of condition. This highlighted that learning conditions affected acquisition of different aspects of the language in a similar manner: The improvement of learning as a consequence of feedback, compared to the implicit and explicit instruction conditions, was observed across nouns, verbs, adjectives, and the marker words.

However, this general improvement in testing performance for the feedback condition did not pertain to accuracy on the syntax testing. Providing participants with no feedback (as in the implicit and explicit conditions) resulted in better performance in recognizing the grammatical structure of the language. This result was anticipated for the explicit condition – where participants are provided with information about the language structure – but not for the implicit condition. Thus, whereas different instructional and learning conditions may improve learning, the improvement may be focused on one property of the language – with a potential dissociation between acquisition of grammar and acquisition of vocabulary, as predicted by models of learning that distinguish cognitive processing systems serving vocabulary and grammar acquisition (Monaghan et al., 2019; Paradis, 2009; Ullman, 2004). These results are also consistent with theories of cross-situational learning that suggest the benefit to learning should be around the vocabulary – where propose-but-verify (Trueswell et al., 2013) or establishing associations between words and potential referents (McMurray et al., 2012), are both strengthened – whereas each of these theories does not make predictions about improvement in learning of grammatical structure in which these words occur. The observation that feedback improvement is limited to vocabulary and not grammar is therefore consistent with these theories.

Contemporary statistical methods enable further detail to be revealed about how learners acquire both language vocabulary and structure (Cunnings, 2012). However, the advantage of these approaches has previously covered their value in identifying individual differences between different language learners (Linck, 2016). We show in our analyses that a further advantage of these mixed-effects models is that the precise context of learning can be taken into account during the dynamic trajectory of learning that participants experience. The statistical methods we deployed enabled us to investigate the local context of learning, as well as the global effects of instruction and feedback on acquisition. The effects of local context during training in our study showed these context effects are complex, and not generic across all aspects of the language being learned. Whereas participants who had previously responded correctly to a trial containing the same verb, noun, or adjective were more likely to be correct in a trial containing the same information. For instance, participants who had previously responded correctly to an utterance containing a particular verb responded more accurately to the next instance that the verb occurred, compared to those who were previously incorrect. This is not surprising, but what was unexpected is that this differed across instruction conditions. The influence of the previous verbs was highest for the implicit condition, then the feedback condition, and then the explicit instruction condition. It seems that, when participants are given no feedback or advance instruction, their previous learning has the greatest influence on their current performance. Instruction interacts in subtle, unanticipated ways with the dynamic learning process.

Taken together, these results show that implicit, associative learning between complex utterances and complex scenes can drive learning of an artificial language, and by extension, demonstrates how naturalistic experience of a second language – embedded in context – can drive acquisition of that language. The results show that acquisition of

vocabulary and grammar – whilst interactive and inter-dependent – are affected distinctly by different instructions. Furthermore, the results show that both explicit instruction about grammatical structure and feedback affect global learning, but that local context interacts in unexpected ways with this information. This means that there is substantial opportunity for contingencies to be exploited during learning situations, as in computer language tutoring systems (Amaral & Meurers, 2011; Heift & Hegelheimer, 2017). The insights available from investigating the local effects provide us with details about what contingent information about learning should be encoded and taken to influence the future exposure to structures being learned by the participant.



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## Appendix

Table S1.

*Comparison between pairs of training blocks*

Group	Comparison	<i>t</i>	<i>df</i>	<i>p</i>
Implicit	Block1_Block2	-1.29	55.30	0.203
	Block2_Block3	-0.81	54.96	0.421
	Block3_Block4	0.18	55.52	0.857
	Block4_Block5	-0.55	55.99	0.584
	Block5_Block6	-1.02	54.94	0.311
	Block6_Block7	0.32	54.52	0.748
	Block7_Block8	-0.03	55.10	0.975
	Block8_Block9	-0.57	54.68	0.573
	Block9_Block10	-0.38	55.96	0.704
	Block10_Block11	-0.10	55.98	0.917
	Block11_Block12	0.17	55.84	0.867
Feedback	Block1_Block2	-2.94	48.46	0.005
	Block2_Block3	-0.04	59.52	0.970
	Block3_Block4	-0.70	59.06	0.487
	Block4_Block5	-0.93	58.53	0.355
	Block5_Block6	-0.38	58.94	0.706
	Block6_Block7	-0.64	59.16	0.525
	Block7_Block8	-0.62	59.67	0.536
	Block8_Block9	0.25	59.48	0.806
	Block9_Block10	-0.11	59.77	0.910

Explicit	Block10_Block11	0.08	59.49	0.939
	Block11_Block12	0.32	59.99	0.748
	Block1_Block2	-0.62	54.83	0.540
	Block2_Block3	-1.09	57.96	0.279
	Block3_Block4	-1.03	56.83	0.307
	Block4_Block5	0.13	57.14	0.901
	Block5_Block6	-0.78	56.11	0.437
	Block6_Block7	-0.07	58.00	0.948
	Block7_Block8	-0.30	58.00	0.769
	Block8_Block9	-0.47	57.95	0.643
	Block9_Block10	-0.49	57.71	0.627
	Block10_Block11	0.37	57.21	0.710
	Block11_Block12	0.00	58.00	1.000

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