Simulating proficiency and exposure effects on cross-language structural priming in simultaneous bilinguals

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Abstract

Bilingual speakers are more likely to use a syntactic structure in one language if they have recently encountered that same structure in another language. This cross-language structural priming effect is predicted to be positively modulated by second language proficiency according to a developmental account by Hartsuiker and Bernolet (2017). We propose to extend this account from *sequential* bilinguals to *simultaneous* bilinguals. In this latter group, syntactic structures develop in parallel and can integrate from the onset. Therefore, we do not expect proficiency or other measures of development, such as exposure, to modulate cross-language structural priming in these bilinguals. In simulated cross-language structural priming experiments, we explored how proficiency affects priming of transitives. We use an implicit learning model of sentence production to model the simultaneous English-Spanish bilinguals in these simulations. Furthermore, we investigated whether the priming effect is modulated by exposure to the non-dominant language, which only Kutasi et al. (2018) also analyzed. We found no evidence for any modulating effects for either proficiency or exposure, which is in line with the previously reported behavioral result of Kutasi et al. (2018). Together, our modeling results and Kutasi et al.'s (2018) behavioral results support an extended version of the developmental account of cross-language structural priming that predicts a modulating effect of proficiency in *sequential* bilinguals, but not in *simultaneous* bilinguals.

Keywords: cross-language structural priming; multilingualism; proficiency; syntax; error-driven implicit learning

Introduction

Structural priming is the tendency of speakers to reuse syntactic structures that they have recently encountered. It occurs in real life discourse and it is a phenomenon that can give insight in how syntax is represented in the human mind. Structural priming has been demonstrated to occur between different languages. In a study on priming of transitives in Spanish-English bilinguals (Hartsuiker, Pickering, & Veltkamp, 2004), for example, participants were more likely to use a passive target sentence in English (e.g., "*The bottle is hit by the bullet*") after hearing a passive Spanish sentence ("*El camión es perseguido por el taxi*") than after hearing an active Spanish sentence ("*El taxi persigue el camión*"). This shows that syntactic representations can be shared between languages. Cross-language structural priming has been investigated in pairs of relatively similar languages such as English and Spanish, but also in languages from different families such as English and Korean (Shin & Christianson, 2009). Cross-language priming has been demonstrated for different syntactic structures such as transitives, datives (Loebell & Bock, 2003) and genitives (Bernolet, Hartsuiker, & Pickering, 2013). It has been shown to occur not only in adults but also in children (Vasilyeva et al., 2010).

Different accounts of structural priming have been proposed. One account explains it as the result of residual activation of syntactic representations and combinatorial nodes (Pickering & Branigan, 1998). Another account explains it as the result of error-driven implicit learning (Chang, Dell, & Bock, 2006; Chang, Dell, Bock, & Griffin, 2000). In this account, prediction error leads to strengthening of connections between representations that support the use of a syntactic structure, which in turn leads to increased production of that structure, which is measurable in behavioral experiments as a priming effect.

Different models of within-language structural priming have been implemented. Specifically, the Dual-path model (Chang, 2002) was used to simulate monolingual priming of transitives in English (Chang et al., 2006) and of datives in German (Chang, Baumann, Pappert, & Fitz, 2015). It has also been extended to a bilingual model, which was used to study cross-linguistic transfer (Tsoukala, Frank, Van Den Bosch, Kroff, & Broersma, 2021) and code-switching (Tsoukala, Broersma, Van Den Bosch, & Frank, 2021), and it is the only model in which cross-language structural priming has been demonstrated (Khoe, Tsoukala, Kootstra, & Frank, 2020). A hybrid model by Reitter, Keller, and Moore (2011), in which priming is primarily activation-based, has been used to simulate priming in one language but not between different lan-

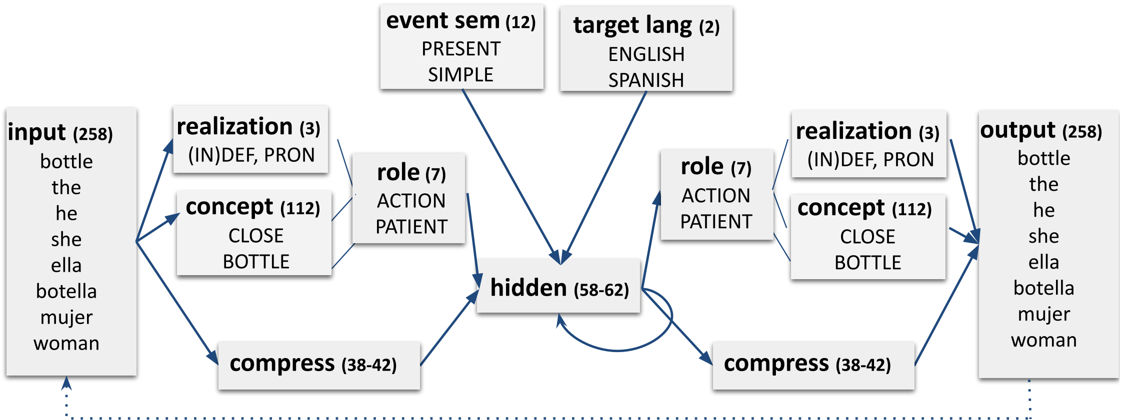

Figure 1: **Bilingual Dual-path.** The model is a next-word prediction network that converts messages into sentences. It is an simple recurrent network-based model (the lower path, via the 'compress' layers) that is augmented with a semantic stream (upper path) that contains information about concepts, thematic roles, event semantics, and the target language. The number of units per layer is shown in parentheses. The numbers of units for the hidden and compress layers vary across simulations. (Figure adapted from Tsoukala et al., 2017)

guages.

It is still an open question how second language (L2) proficiency affects cross-language structural priming. Hartsuiker and Bernolet (2017) have hypothesized that as L2 learners become more proficient, their L2 syntactic representations become more integrated with the representations that they already have for their native language (L1). In this developmental account, the increased integration will then result in increased cross-language structural priming.

In a number of cross-language structural priming studies, proficiency or amount of exposure to the L2 were investigated as predictors of the strength of the priming effect. In four cases, increased cross-language structural priming was found for more proficient participants. The results presented by Bernolet et al. (2013) revealed a positive effect of proficiency on the strength of priming between Dutch and English genitives. A reanalysis by Hartsuiker and Bernolet (2017) of an experiment performed by Schoonbaert, Hartsuiker, and Pickering (2007) also revealed that cross-language priming of datives in Dutch-English bilinguals was stronger for participants who were more proficient in their L2. Similarly, Favier, Wright, Meyer, and Huettig (2019) found that proficiency positively modulated priming of datives and passives from Irish to English. In their investigation of priming between Korean and English transitives, Hwang, Shin, and Hartsuiker (2018) found a priming effect that increased in magnitude as participants were more proficient in their L2, English. In contrast, three other studies did not yield evidence that proficiency modulates priming. The results reported by Hartsuiker, Beerts, Loncke, Desmet, and Bernolet (2016) for priming of relative clause attachment and of datives in multilingual speakers of Dutch (L1), French (L2), English (L2), and German (L2) did not reveal such an effect. Similarly, the results reported by Kutasi et al. (2018) for English and Gaelic transitives did not reveal any effect of either proficiency or exposure. Huang et al. (2019) also found no correlation between self-rated proficiency and the priming effect of datives in trilingual speakers of Mandarin, Cantonese, and English.

These conflicting results might be partly explained by considering the type of bilinguals that were involved in the studies. Whereas all but one of the participants in Kutasi et al.'s (2018) study were *simultaneous* bilinguals, the participants in the other studies were all or in majority *sequential* bilinguals. In our interpretation of the developmental account by Hartsuiker and Bernolet (2017), proficiency is expected to affect cross-language structural priming in *sequential* bilinguals, who start learning a second language after they have acquired their L1, but not in *simultaneous* bilinguals, who acquire their two languages at the same time. These simultaneous bilinguals would develop syntactic representations for both languages at the same time, which could integrate from the onset. The results of the study by Kutasi et al. (2018) is in line with this extended account, as they did not reveal an effect of either proficiency or exposure in the non-dominant language on cross-language structural priming.

While the number of behavioral studies on the effect of proficiency on cross-language structural priming is growing, proficiency differences have not been studied using implemented models of cross-language structural priming. In the above mentioned study by Khoe et al. (2020), the aim was to model balanced simultaneous bilinguals, and the models were therefore trained using approximately equal numbers of sentences in the two languages, that varied only minimally.

In the present work we explore the effect of proficiency and exposure in the non-dominant language on cross-language structural priming in simultaneous bilinguals, whom we model using an implicit learning model of sentence production. We do this by varying the amount of input in the two different languages that the model receives during training. We then perform cross-language structural priming experiments with these model instances as participants. We analyse the results of these experiments to determine whether proficiency or exposure in the non-dominant language modulate cross-language structural priming in the model.

Method

Model

We trained instances of the Bilingual Dual-path model[1] of sentence production (Figure 1) on miniature versions of English and Spanish to serve as simulated participants in cross-language priming experiments. The Bilingual Dual-path model extends the meaning path of the original Dual-path model (Chang, 2002) with a target language layer that indicates the intended output language.

The training input to the model consists of sentences in two artificial languages that are paired with messages that encode their meaning (see examples below, under: Artifical languages). The model instances receive input in both languages from the start of training to simulate simultaneous English-Spanish bilinguals, who start acquiring both English and Spanish from infancy. The model learns to convert a message into a sentence by predicting sentences word by word and adjusting its connection weights based on prediction error using back-propagation. A difference between the Dual-path architecture and other Recurrent Neural Networks is that the network has connections with fixed weights between concepts and roles of the message to be expressed.

Artificial languages The artificial versions of English and Spanish[2] that we used include the same nine sentence types for each language: Animate intransitive, Animate with-intransitive, Inanimate intransitive, Locative, Transitive (in active or passive form), Cause-motion, Benefactive transitive, State-change, and Locative alternation[3]. The two languages together have 275 unique lexical items. In addition to nouns, verbs, adjectives, determiners, and prepositions, these lexical items include inflectional morphemes such as a past tense marker (Spanish: '-pas'; English: '-pst') and a past participle marker (Spanish: '-prf'; English: '-par'). The message semantics contain 121 concepts and 7 thematic roles. Only singular verbs, pronouns, nouns, and adjectives were used. Verbs and pronouns were always in third person form.

Of the transitives in our artificial languages, 75% were actives and 25% were passives. This skew in favor of actives is more in line with the frequencies of these constructions in natural language than the balanced frequencies of actives and passives that was used by Khoe et al. (2020).

In the training and test input, any message that can be expressed using two different syntactic structures has a strong bias towards one of those structures. This was implemented by creating differences in activation of thematic roles based on how each structure emphasizes those roles in the sentence. Biasing towards an active sentence (1, 2), for example, was done by giving the agent a higher activation (X:1) than the patient (Y:0.5 or Y:0.75). In the same way, a bias towards a passive sentence (3, 4) was achieved with a higher activation for the patient (Y:1), than for the agent (X:0.5 or X:0.75). In the priming experiment, we gave the de-emphasized roles in target messages an activation of 0.75.

1. Spanish Active: el padre romper -pas la botella .
   X = def, FATHER, M;
   ACTION-LINKING = BREAK;
   Y = def, BOTTLE;
   EVENT-SEM = **X:1, Y:0.5**, PAST,
   SIMPLE, ACTION-LINKING;
   TARGET-LANG = es

2. English Active: the father break -pst the bottle .
   [...];
   EVENT-SEM = **X:1, Y:0.5**, [...];
   TARGET-LANG = en

3. Spanish Passive: la botella es romper -prf por el padre .
   [...];
   EVENT-SEM = **X:0.5, Y:1**, [...];
   TARGET-LANG = es

4. English Passive: the bottle is break -par by the father .
   [...];
   EVENT-SEM = **X:0.5, Y:1**, [...];
   TARGET-LANG = en

Model training and testing We trained 120 model instances that function as simulated participants in our experiments. To simulate proficiency differences in the English-Spanish models, we trained the models with a percentage of sentences in Spanish, the non-dominant language, sampled from a truncated normal distribution (lower bound: 0%, upper bound: 50%) with a mean of 35%, and a standard deviation of 15, and the rest was in English. A set of 8,000 unique message-sentence pairs was generated for each model participant. 80% of these sentences were used for training, while 20% were set aside for testing the accuracy of the model. Following Chang et al. (2006), the message was excluded from 25% of training pairs. The models iterated over their training sets 16 times. After each of these 16 epochs, model accuracy was tested using the test set. The training set was shuffled at the beginning of each epoch.

Model configuration Differences between individual simulated participants were also created through small variation in model parameters. The number of hidden-layer units was sampled from a uniform distribution between 58 and 62, while the number of compress layer units was sampled from a uniform distribution between 38 and 42. The fixed weight value for concept–role connections was sampled from a uniform distribution between 13 and 17.

Priming experiment

Simulated participants Table 1 gives an overview of measures of proficiency and exposure for the non-dominant lan-

[1] The Bilingual Dual-path model can be downloaded from: `https://gitlab.com/yhkhoe/bilingual-dual-path/-/tree/ICCM2021`

[2] The files that the model requires to generate the artificial language input, and the input for the priming experiment can be found here: `https://github.com/khoe-yh/cross-lang-struct-priming`

[3] Examples for these sentence types can be found in Chang et al. (2006)

Table 1: Meaning accuracy, syntactic accuracy, and input in the non-dominant language (Spanish) for the 120 simulated participants in our experiment.

	Mean	Standard Deviation
Meaning accuracy	59.8%	20.0
Syntactic accuracy	95.1%	8.7
Input	29.8%	11.3

guage (Spanish) of the 120 simulated participants in our experiment. We operationalized proficiency in the non-dominant language as either syntactic accuracy or meaning accuracy in that language. Syntactic accuracy was measured as the percentage of sentences out of all test sentences for which all the words had the correct part of speech. Meaning accuracy was measured as the percentage of syntactically accurate sentences that convey the target message without any additions. Exposure to the non-dominant language was operationalized as the percentage of sentences in the training input in that language.

The standard deviations of these measures suggest that the heterogeneity in our sample of simulated participants is comparable to that in the participant samples of Kutasi et al. (2018) and Favier et al. (2019). Both studies report self-rated proficiency measures on a 7-point scale. The standard deviations for these measures ranged from 0.51 to 1.00 in the study by Kutasi et al. (2018), and from 0.61 to 1.12 in the study by Favier et al. (2019).

Experimental trials In addition to the training and test sets, we generated a single set of experimental trials that was used to perform the priming experiment on all of the model participants. Each trial consisted of a combination of a unique prime sentence and a unique target message that did not have any semantic overlap in terms of their verb, agent, and patient. Following Kutasi et al. (2018), we only use prime sentences in the non-dominant language, which in our case is Spanish. We had equal numbers of trials with active and passive primes, and equal numbers of trials with active- and passive-bias target messages.We had 50 prime-target combinations that all occurred as each of the 4 different trial types. Each experiment thus consisted of 200 trials.

Procedure The priming experiment was performed on the models after 16 training epochs. As was done by Chang et al. (2006) and Chang et al. (2015), we presented the models with prime sentences without a message, while learning was turned on in the model. After each prime, a response was elicited from the model by presenting it with a target message.

We aimed to simulate a cross-language structural priming effect that is similar in strength to what is found experimentally. Since the strength of the effect is largely determined by the learning rate, we used a range of different learning rates. In Khoe et al. (2020), a learning rate of 0.2 was used during the experiment. This resulted in priming effects that were stronger than such effects found in behavioral experiments. For the present study, we therefore used learning rates between 0.02 (the learning rate at the end of training) and 0.06 (the average of the learning rates at the start and the end of training).

After each trial, the connection weights were reset to the values they had before starting the priming experiment. The state in which the model encounters each trial was thus the same for all of the trials, hence, there was no between-trial priming or any other learning effect during the experiment. This means that we did not need to (pseudo-)randomize the order of the trials across model participants.

Table 2: Percentage of included responses, and percentage of passive sentences produced after a passive prime or after an active prime, at learning rates of 0.02, 0.04 or 0.06.

	Learning rate		
	0.02	0.04	0.06
Responses included	61.0%	60.8%	60.4%
Passives after passive prime	37.6%	38.0%	38.5%
Passives after active prime	37.4%	37.5%	37.4%

Results

Descriptive results

Our analyses only included responses that correctly expressed the target message, with either an active or a passive structure. However, we disregarded errors involving definiteness of articles or missing periods. Table 2 shows the percentage of responses that was included on the basis of these criteria for each of the three learning rates at which the experiment was run. The table also shows the percentage of these responses that were passives after a passive prime or after an active prime.

Bayes Factor analyses

We analyzed the data from our experiment with Bayesian logistic mixed-effects models, with a logit link function, using the function brm from the package brms (Bürkner et al., 2017; Bürkner, 2018, version 2.12.0) in R (R Core Team, 2013, version 3.5.1). These analyses were not pre-registered and should therefore be considered exploratory.

The models predicted a binary dependent variable, IS PASSIVE, that indicated whether the sentence that the model produced was passive (1), or not (0). The null model included three centered continuous predictors: MEANING ACCURACY, SYNTACTIC ACCURACY, and INPUT, and two contrast-coded predictors PRIME STRUCTURE (Active = -0.5, Passive = 0.5), and TARGET-MESSAGE BIAS (Active = -0.5, Passive = 0.5). We fit random intercepts for model participants and items, as well as by-participant random slopes for PRIME STRUCTURE. The alternative models only differed from the null model in including an interaction between PRIME STRUCTURE and either MEANING ACCU-

Table 3: Bayes Factors that compare models including interactions between each of the three predictors of interest and Prime Type with a null model without any such interaction, for priming experiments with a learning rate of 0.02, 0.04, or 0.06, where the prior for the interaction had a standard deviation of either 0.5 or 1. A Bayes Factor smaller than 1 favors the null model whereas a Bayes Factor larger than 1 favors the alternative model that includes an interaction.

Learning Rate	Standard Deviation			
	0.25	0.5	0.75	1
	Meaning accuracy			
0.02	0.111	0.052	0.035	0.025
0.04	0.091	0.046	0.032	0.027
0.06	0.124	0.051	0.035	0.025
	Syntactic accuracy			
0.02	0.377	0.175	0.136	0.118
0.04	0.273	0.160	0.105	0.077
0.06	0.329	0.179	0.103	0.077
	Input			
0.02	0.237	0.105	0.075	0.058
0.04	0.169	0.094	0.056	0.044
0.06	0.212	0.079	0.057	0.044

RACY, SYNTACTIC ACCURACY, or INPUT. We computed Bayes Factors that compare the null model to these alternative models.

We calculated Bayes Factors using bridge sampling (Bennett, 1976; Meng & Wong, 1996; Gronau et al., 2017), with four chains and 8000 iterations, including a warm-up phase of 2000 iterations. Because an uninformative prior for the predictor of interest can make a Bayes Factor biased towards the null model (Lee & Wagenmakers, 2014), we report Bayes Factors across four different values of the standard deviation (σ) for the prior of the interaction of interest (Normal(0, σ)), ranging from a value appropriate for an informative prior (i.e., $\sigma = 0.25$) to a value appropriate for a regularizing prior (i.e., $\sigma = 1$). Regularizing priors (Normal(0,1)) were used for all other predictors in our models. These priors give a minimal amount of information with the objective of yielding stable inferences. Prior means were 0, and did thus not bias towards specific effects. The only exception to this was the TARGET-MESSAGE BIAS predictor for which we excluded negative values by using a prior with a Gamma distribution (Gamma(1, 0.5)).

Table 3 shows that the Bayes Factors are all smaller than 1, and thus provide evidence in favor of the null model. Based on the scale proposed by Jeffreys (1998), we interpret this evidence as ranging from anecdotal to very strong. As expected, when a smaller standard deviation is used for the prior, the Bayes Factors are mostly closer to 1, and thus provide less conclusive evidence for the null model. The Bayes Factors do not suggest a clear effect of learning rate on the strength of the evidence for the null model.

Null model estimates

Because our exploratory analysis does not yield any evidence for modulating effects of proficiency or exposure on priming, we do not report estimates from the analyses that included interactions between PRIME STRUCTURE and any of our three predictors of interest. Instead, we provide a summary of the results from the null models for priming experiments with three different learning rates in Table 4. In line with our expectations, the estimates for the PRIME STRUCTURE predictor are higher for higher learning rates. The credible intervals for the PRIME STRUCTURE predictor contain only positive values at learning rates of 0.04 and 0.06, which indicates strong evidence for a priming effect. At a learning rate of 0.02, the credible interval that includes some negative values indicates weaker evidence for a priming effect.

Discussion

In the present work, we explored whether proficiency or exposure modulate cross-language structural priming in simultaneous bilinguals, simulated using an implicit learning model of sentence production. Our results indicate anecdotal to strong evidence against such modulating effects in the model. This is in line with the results reported by Kutasi et al. (2018). Taken together, those behavioral results and our modeling results provide support for an extended version of the developmental account of cross-language structural priming (Hartsuiker & Bernolet, 2017) that not only predicts a modulating effect of proficiency in *sequential* bilinguals, but that also explicitly predicts the absence of such an effect in *simultaneous* bilinguals.

Limitations and further work

One limitation of our simulations lies in a difference between the languages and syntactic structures involved in our simulated experiments and those in the experiments that Kutasi et al. (2018) conducted. The main question that Kutasi et al. (2018) addressed in their study, was whether cross-language priming can occur for structures with different word order between languages. For this reason, they studied bilinguals who spoke English and Scottish Gaelic, for which active as well as passive word order is different. In contrast, the English and Spanish transitives in our experiments have the same word order between the two languages for both actives and passives. We could therefore come closer to simulating the results from Kutasi et al. (2018) by using the English-Dutch model reported on by Khoe et al. (2020) in which English passives are verb-medial, while Dutch passives are verb-final.

The participants that were involved in the other studies that investigated the possible modulating effect of proficiency on cross-language structural priming were sequential bilinguals. An obvious follow up to the present study is to simulate

Table 4: Summary of the fixed effects in the Bayesian logistic mixed-effects null models with different learning rates ($N =$ 14,633, 14,594, and 14,491, for experiments with learning rates of 0.02, 0.04, and 0.06 respectively).

Predictor	Estimate			95% CrI			P(Est. > 0)		
Learning rate	0.02	0.04	0.06	0.02	0.04	0.06	0.02	0.04	0.06
INTERCEPT	1.04	1.02	0.83	[−0.29, 2.62]	[−0.14, 2.39]	[−0.16, 1.99]	0.93	0.96	0.95
PRIME STRUCTURE	0.52	1.08	1.30	[−0.38, 1.45]	[0.29, 1.91]	[0.49, 2.12]	0.87	1.00	1.00
TARGET-MESSAGE BIAS	27.59	25.16	22.98	[21.91, 34.83]	[20.36, 31.41]	[18.98, 28.03]	1.00	1.00	1.00
MEANING ACCURACY	0.05	0.09	0.08	[−0.06, 0.17]	[−0.00, 0.20]	[0.00, 0.17]	0.81	0.97	0.97
SYNTACTIC ACCURACY	0.01	−0.08	−0.08	[−0.26, 0.29]	[−0.31, 0.15]	[−0.29, 0.13]	0.54	0.26	0.23
INPUT	−0.12	−0.09	−0.07	[−0.27, 0.02]	[−0.22, 0.03]	[−0.18, 0.03]	0.05	0.07	0.09

cross-language structural priming in these sequential bilinguals, and to determine whether proficiency or exposure does modulate priming in these simulations, as predicted by the developmental account of Hartsuiker and Bernolet (2017).

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