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Input and age-dependent variation in second language learning: A connectionist account

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Author Note

This research was funded by an ESRC grant (number ES/J500094/1). Marius Janciauskas and Franklin Chang are members of the International Centre for Language and Communicative Development (LuCiD) at the University of Liverpool. The support of the Economic and Social Research Council [ES/L008955/1] is gratefully acknowledged. We thank James Flege for sharing the Flege, Yeni-Komshian, and Liu (1999) data with us.

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Abstract

Language learning requires linguistic input, but several studies have found that knowledge of second language (L2) rules does not seem to improve with more language exposure (e.g., Johnson & Newport, 1989). One reason for this is that previous studies did not factor out variation due to the different rules tested. To examine this issue, we reanalysed grammaticality judgment scores in Flege, Yeni-Komshian, & Liu's (1999) study of L2 learners using rule-related predictors and found that, in addition to the overall drop in performance due to a sensitive period, L2 knowledge increased with years of input. Knowledge of different grammar rules was negatively associated with input frequency of those rules. To better understand these effects, we modeled the results using a connectionist model that was trained using Korean as a first language (L1) and then English as an L2. To explain the sensitive period in L2 learning, the model's learning rate was reduced in an age-related manner. By assigning different learning rates for syntax and lexical learning, we were able to model the difference between early and late L2 learners in input sensitivity. The model's learning mechanism allowed transfer between the L1 and L2, and this helped to explain the differences between different rules in grammaticality judgment task. This work demonstrates that an L1 model of learning and processing can be adapted to provide an explicit account of how the input and sensitive periods interact in L2 learning.

Keywords: Second language learning; Sensitive period; Age of acquisition; Input-based learning; Connectionist neural network; Language Acquisition

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Linguistic input is critical for language learning. In first language (L1) acquisition, linguistic elements that occur more frequently are easier to learn (Ambridge, Kidd, Rowland, & Theakston, 2015; Bybee, 2006; Dąbrowska & Lieven, 2005; Marchman, Wulfeck & Weismer, 1999; Phillips, 2006) However, the relationship between input frequency and second language (L2) learning is less clear. Several studies have reported that the amount of language input – as measured, for example, by years living in L2 environment – does not correlate highly with the acquisition of grammar and morphology in adult L2 learners who started learning the L2 at different ages (DeKeyser, Alfi-Shabtay, & Ravid, 2010; DeKeyser, 2000; Johnson & Newport, 1989; Lee and Schachter, 1997; McDonald, 2000; Oyama, 1978; Patkowski, 1980; Andringa, 2014). Given that languages cannot be learned without linguistic input, these findings are counterintuitive and at odds with the notion that input plays an important role in L2 theories (N. Ellis 2013; MacWhinney, 2008). This discrepancy in the role of input suggests that differences exist in the mechanisms that are used by L1 and L2 learners, and the present study examines whether these differences can be explained in a unified way.

Input effects in L2 learning are modulated by the critical or sensitive period, the time window approximately between birth and puberty during which language learning is most effective (Knudsen, 2004; Lenneberg, 1967). This sensitive period effect is modulated by the age at which language learners begin learning the L2. As age of acquisition (AoA) increases, the ability to learn the L2 decreases (Flege, Yeni-

Komshian, & Liu, 1999; Johnson & Newport, 1989). While many of these AoA effects are found in explicit tasks, similar effects have been found in implicit tasks such as timed judgements (R. Ellis, 2005) and ERP studies (Weber-Fox & Neville, 1996). Similar AoA effects are found in L1 learning in deaf learners of sign language (Boudreault & Mayberry, 2006; Mayberry, 2010; Mayberry & Eichen, 1991) and international adoptees (Gardell, 1979; Gauthier & Genesee, 2011; Hyltenstam, Bylund, Abrahamsson, & Park, 2009). A wide range of social, motivational, input, and biological factors have been proposed to explain this reduction in learning ability (for a balanced review, see DeKeyser & Larson-Hall, 2005). For these factors to explain the AoA effects, there needs to be a gradual accumulation of the negative impact of these factors as the learner gets older (e.g., motivation to learn the L2 decreases for each year of age). Understanding the mechanism that could explain the gradual reduction in L1/L2 learning in such diverse circumstances is an important goal for understanding language learning.

A classic study that investigated the sensitive period is that of Johnson & Newport (1989). The authors tested English morphosyntactic grammar knowledge in Korean and Chinese immigrants in the US. They examined whether the English abilities of these L2 speakers could be predicted from the age at which they started learning English in immersion settings (3 to 39 years: *age of acquisition*, AoA), and years spend in the US (7 to 30 years; *length of exposure*, LoE). The participants' L2 knowledge was assessed via a grammaticality judgment task, in which they indicated whether a given English sentence was grammatical (1a) or not (1b).

(1a) The farmer bought two pigs at the market

(1b) The farmer bought two pig at the market

The authors found that the performance dropped as AoA increased, showing that their ability to learn grammatical knowledge depended on the age at which they started learning the L2. However, they found no correlation between LoE and grammaticality judgment scores ($r = .16$, $p > .05$) and this has been replicated in several other studies (DeKeyser et al., 2010; DeKeyser, 2000; Lee and Schachter, 1997; McDonald, 2000; cf. Flege et al., 1999). The lack of LoE effect is an important issue, as it contradicts the assumption that language ability should increase as more input is experienced (N. Ellis, 2013).

One reason why LoE effect was not observed in Johnson and Newport's (1989) study could be related to the variation among different rules used in test sentences. The authors examined grammatical knowledge of 12 different morphosyntactic rules (Table 1). For example, sentence (1b) violated the plural rule use that required adding –s to the plural noun 'pig'. Their data suggests that as AoA increased, the average grammatical knowledge dropped at different rates for different rules. Late learners performed worse with determiners and plural rules, whilst past tense and 3rd person singular rules seemed to be easier to master. Similar rule-specific effects have also been observed in several other studies (DeKeyser, 2000; Flege et al., 1999; Johnson, 1992; McDonald, 2000). Since their analyses collapsed the data over different rules, this within-subject variation could have obscured the effect of between-subject factors like LoE.

Table 1*: Examples of test items used to test the knowledge of 5 different grammar rules (ungrammatical rule use underlined)*

Rule	Grammaticality	Example Test Item
Determiner	Grammatical	Tom is reading the book in the bathtub

	Ungrammatical	Tom is reading __ book in the bathtub
Plural	Grammatical	The farmer bought two pigs at the market
	Ungrammatical	The farmer bought two pig at the market
Particle verbs	Grammatical	The horse jumped over the fence yesterday
	Ungrammatical	The horse jumped the fence over yesterday
3rd person singular	Grammatical	Every Friday our neighbor washes her car
	Ungrammatical	Every Friday our neighbor wash her car
Past tense	Grammatical	Last night the old lady died in her sleep
	Ungrammatical	Last night the old lady die in her sleep

To understand the role that rule variation plays in sensitive period studies, we reanalysed Flege et al. (1999) study, which was based on Johnson and Newport's (1989) original study but had a much larger sample of 240 Korean learners of English (compared to 46 participants in Johnson and Newport's study). To preview the findings, our analysis showed a significant effect of rule, which means that these learners were consistently better at judging grammaticality of some rules than others (consistent with rule differences in various L1/L2 studies; Leonard, Caselli, Bortolini, McGregor & Sabbadini, 1992; McDonald 2000; Mizumoto, Hayashibe, Komachi, Nagate & Matsumota, 2012; Rescorla & Roberts, 2002). One explanation for the rule variation is the differences in frequency with which those rules occur in the input. Higher frequency rules are thought to yield to better learning outcomes (N. Ellis, 2002; Ambridge, Kidd, Rowland, & Theakston, 2015; Lieven, 2010) and this predicts that L2 learners should be more accurate at judging the accuracy of higher frequency rules. Another explanation is that rules that are similar across the L1 and L2 are easier to learn than those that are different (L1-transfer/interference, (Bernolet,

Hartsuiker, & Pickering, 2013; Foucart & Frenck-Mestre, 2012; Hartsuiker, Pickering, & Veltkamp, 2004; Ionin & Montrul, 2010; MacWhinney, 2005; Sabourin, Stowe, & de Haan, 2006). One challenge for transfer accounts is that there is no agreement about how to best measure L1-L2 similarity and it would be difficult to augment the Flege et al. analysis with an objective measure of L1/L2 similarity. Therefore, to contrast frequency and transfer accounts, we performed a corpus study to quantify the input frequencies for some of the rules in Flege et al.'s study and used these frequencies in the reanalysis to understand the differences in L2 learners' performance with different rules. If the frequencies positively predicted performance in grammaticality judgment task, it would support frequency-based approaches. If this was not the case, then that would provide indirect evidence for alternative accounts like language transfer. Finally, we used a connectionist model of L1 language acquisition to see if we could model the findings in the reanalysis to understand how input frequency and language transfer might work in L2 language acquisition.

Corpus analysis

To make a grammaticality judgment, participants read a sentence and then classify it as either grammatical or ungrammatical. One way to make this decision would be to use knowledge about the transitions between words. For example, in the sentence *The farmer bought two pig at the market,* the transition between *two* and *pig* makes the sentence ungrammatical. One way to detect this ungrammatical transition would be to test if the frequency of the bigram *two pig* was below a threshold. However, since the raw bigram frequency can differ for different words (e.g., *twenty-three pigs* is a rare grammatical bigram), it can be hard to distinguish grammatical

and ungrammatical transitions based on raw bigram frequency knowledge. An alternative statistic that automatically adjusts for this is forward conditional probability (CP), which is the raw frequency of the bigram divided by the frequency of the previous word, e.g., CP = frequency of *twenty-three pigs*/ frequency of *twenty-three*. There is a lot of evidence that CPs can explain infants' language learning behavior (Aslin, Saffran, & Newport, 1998; Gomez & Gerken, 2000), as well as experimental results in children/adults (Jurafsky, 2003; Levy, 2008; Monaghan, Chater, & Christiansen, 2005; Thompson & Newport, 2007). Critically, there is evidence suggesting that L2 learners show a similar sensitivity to forward CPs as L1 learners in an on-line task (Huang, Wible, and Ko, 2012). In this work, we explore whether forward CPs can explain the differences in rule performance in Flege et al.'s study. Our approach does not imply that people do not also extract other statistics such as backward CPs (e.g., frequency of *twenty-three pigs* divided by frequency of *pigs*) or 4-grams and used them to aid language use (Bannard & Matthews, 2008; Chang, Lieven, & Tomasello, 2008; French, Addyman, & Mareschal, 2011; Huettig & Mani, 2016). The goal of this analysis is to provide some evidence that rule differences are related to at least one input frequency-related measure.

To compute these statistics, we used child-directed speech from CHILDES online child language database (MacWhinney, 2000) and adult input from a spoken subset of the Corpus of Contemporary American (COCA; Davies, 2010). From CHILDES, we used the mothers' utterances (a total of 591,762 in 32 North American corpora (Bates, Bretherton & Snyder, 1988; Bernstein-Ratner, 1984; Bliss, 1988; Bloom, 1970; Bloom, 1973; Bohannon & Marquis, 1977; Brent & Siskind, 2001; Brown, 1973; Clark, 1978; Demetras, 1989; Feldman & Menn, 2003, Gleason, 1980; Hall, Nagy and Linn, 1984; Higginson, 1985; Kuczaj, 1977; Morisset, Barnard &

Booth, 1995; Ninio, Snow, Pan & Rollins, 1994; Peters, 1987; Post, 1994; Rollins, 2003; Sachs, 1983; Soderstrom, Blossom, Foygel & Morgan, 2008; Suppes, 1974; Valian, 1991, van Houten, 1986; Warren-Leubecker, 1982). The remaining corpora were Cornell, MacWhinney, McCune, McMillan, Snow, and Tardif (MacWhinney, 2000). In these corpora, mothers are talking to children up to 8 years of age, as well as other adults/children (e.g., investigator, father, grandparents, siblings, uncles/aunts, babysitter).

Conditional probabilities (CPs) depend on rule frequencies. To compute these frequency counts, we created search terms that were based on the items used to test grammaticality in Flege et al.'s study. For example, determiner (DET) knowledge was tested with an ungrammatical sentence like *The boy is helping the man to <u>build house</u>*, which requires the knowledge that the verb *build* must be followed by a determiner *the* before using the noun *house*. Thus to judge the grammaticality of the sentence participants could use knowledge about how likely a verb is followed by a determiner. To calculate this, we extracted the frequency of verbs followed by determiners (verb-determiner) and the overall frequency of verbs (verb frequency) using the corpora tiers that were coded for syntactic categories and morphology. The DET rule CP was then calculated by dividing verb-determiner frequency by the verb frequency and this tells us out of all verb uses in this corpus, what proportion were followed by a determiner. In addition to the determiner rule, we also collected CPs for four other rules: plural (PL), particle use in phrasal verbs (PAR), third person singular verb inflection (3PS) and past tense (PST). The PL CP was calculated by dividing the number of plural nouns by the total number of nouns, which provided a measure of how likely a plural rule was to be encountered in the input compared to other noun forms. The PAR CP was thus calculated by taking the frequency of verbs

followed directly by a particle and dividing it by the total number of verbs, and this probabilistic knowledge could help to identify non-adjacent particles as ungrammatical (e.g., *The man climbed the ladder up carefully*). The 3PS CP was calculated by dividing the number of verbs in 3rd person singular form by the total number of verbs, and this could help identify how likely a 3PS form was to be encountered. The PST CP was calculated by dividing the number of past tense verbs by the total number of verbs, and this provides information about how likely past tense was in general. Table 2 shows the implemented CLAN search terms (MacWhinney, 2000) and the corresponding raw frequency for each rule (number of utterances that matched).

Table 3 shows rule conditional probabilities (CP) for the same rules. It also includes rule CPs extracted from a subset of the COCA corpus to show that the results are consistent across different corpora. The correlation between rule CPs in the CHILDES and COCA corpora was high ($r = 0.74$), which means that the frequency of these five rules was similar across both children- and adult-directed speech. This correlation is due to the fact that the CPs for the DET/PL rules are higher than the 3PS/PST rules in both corpora, but the rank order within these rules is not always consistent. Since the COCA corpus was a transcription of television news programs (e.g., discussions of the Peacemaker missile system), we view this as being less typical of the input that L2 learners are generally exposed to in day-to-day settings. Since the CHILDES corpora include conversational speech between adults and other adults, as well as children up to 8 year of age, we view them as a better measure of the frequent word and structures that L2 learners are likely to use and know, and hence the following analyses used the rule CPs from the CHILDES corpora only.

Table 2

Corpora search terms and raw frequency (number of matching utterances in CHILDES) for different rules

Rule	Search Term (example utterances)	Raw frequency
DET	+tMOT +t%mor +u +sdet|* (see if we can build a tower)	159107
PL	+tMOT +t%mor +u +sn|*-PL (that's what the chickens say)	40171
PAR	+tMOT +t%mor +u +sadv|* (you can sit some people down here)	133958
3PS	+tMOT +t%mor +u +sv|*-3S (the square goes in the square)	16570
PST	+tMOT +t%mor +u +sv|*-PAST (look what happened here)	6049
VERBDET	+tMOT +t%mor +u +sv|*^det|* (see if we can build a tower)	42038
VERBPAR	+tMOT +t%mor +u +sv|*^adv|* (go ahead)	28571
VERB	+tMOT +t%mor +u +sv|* (look at that)	334191
NOUN	+tMOT +t%mor +u +sn\\|* (it's a chicken)	320650

Table 3

Rule CP in CHILDES and COCA corpora

Rule	Formula used to calculate Rule CP	CHILDES CP	COCA CP
DET	VERBDET/VERB	0.126	0.14
PL	PL/NOUN	0.125	0.21
PAR	VERBPAR /VERB	0.085	0.13
3PS	3PS/VERB	0.05	0.08
PST	PST/VERB	0.018	0.11

This corpus analysis has provided two measures of frequency for each rule: raw frequency and CP. In the next section, we will test these different measures to see which best explain the rule differences in the Flege et al. study. If there is a significant effect of either frequency measure, then that would suggest that the 240 participants in that study had consistent better knowledge of rules with particular frequencies properties.

Flege et al. (1999) reanalysis

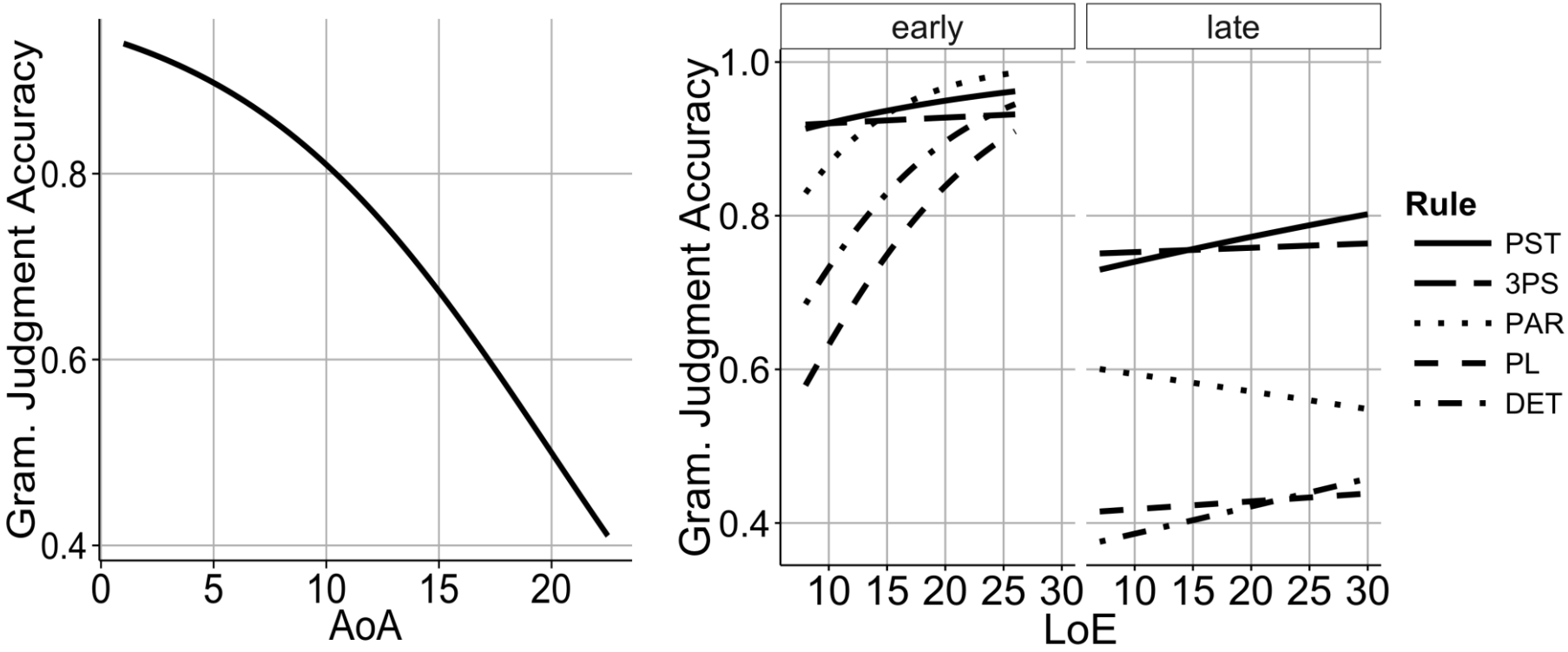
Flege and his colleagues investigated English grammar knowledge of 240 Korean immigrants living in the United States who had migrated at the ages between 1-23 (mean=12, sd=5.9). At the time of testing their average age ranged from 17-47 (mean= 26, sd=6). All participants had lived in US from 7-30 years (mean=14.6, sd=4.6). Half of the participants were males or females and different AoA groups had representative sample of participants with different LoE (Table 4).

Table 4*: Number of participants in different AoA and LoE groups*

LoE groups	AoA groups			
	1-5	6-11	12-17	18-22
7-14	6	35	54	32
15-30	42	37	18	16

The authors tested morphosyntactic knowledge for 10 rules using a grammaticality judgment test consisting of 144 sentences. The items were designed so that each grammatical sentence had an ungrammatical counterpart that violated a

certain grammar rule (see Table 1 for examples). The participants heard a recorded sentence and were required to indicate if it was permissible in the English language. Consistent with Johnson and Newport's (1989) results, Flege et al. (1999) found that the scores for different rules varied with AoA, but their analysis involved separate anova models for each rule. The novel feature of our reanalysis is to include rule-related predictors in the model to factor out rule variation from individual variation in LoE and AoA. In addition, we used logistic mixed effects models where we could predict binary grammatical judgments for individual sentences while factoring out participant and test item variation. Since our goal was to examine how input variation influenced the acquisition of different L2 rules, we excluded the data from native English speaker and only used the data from the 5 rules (DET, PL, PAR, 3PS, PST) that we had objective and comparable search terms. Since grammatical sentences must conform to multiple grammatical rules, we used the ungrammatical test items, because correct rejection of these rules is more likely to relate to the rule that was used to make the sentence ungrammatical. There were 8 test sentences for each rule (except for PAR which only had 6 items) and overall there were 9,120 judgements for the 38 test items over 240 participants.



(a) **(b)**

Figure 1. (a) Effect of AoA on grammaticality judgment scores; (b) Effect of LoE on different rules in early (<12) and late (>12) AoA learner

To replicate the earlier studies that found no effect of length of exposure, we first analysed the data without including any rule-related predictors. Grammaticality judgments (grammatical = 1, ungrammatical = 0) were predicted by a logistic mixed model with AoA crossed with LoE (all predictor variables were centered) and participant and test sentences as random effects. The maximal model that converged contained AoA crossed with LoE as random slopes for test sentence (R version 3.0.2; Barr, Levy, Scheepers, & Tily, 2013). Likelihood-ratio tests were used to compare models and a chi-squared statistic for the comparison was used to compute p-values. The same approach was used for all of the models in this paper. As seen in Figure 1a, there was a significant effect of AoA which suggests an age-related reduction in L2 learning ability (β = -0.2, SE = 0.02, $\chi^2(1) = 65.98$, $p < .001$). There was no effect of LoE ($p = 0.17$) and no interaction between the two variables ($p = 0.25$). Thus, we find that the years of input is not a strong predictor of grammaticality judgments when the variability between rules is treated as unexplained variance.

Next, we added rule as a categorical factor (fully crossed with age of acquisition and length of exposure) to see if L2 learners showed consistent patterns in their knowledge for certain rules. The maximal model that converged contained no random slopes. There was a significant negative effect of AoA (β =-0.161, SE=0.02, $\chi^2(1)=177.51$, $p<0.001$), a positive effect of LoE (β =-0.001, SE=0.03, $\chi^2(1)=4.13$, $p=0.042$) and a negative effect of rule ($\chi^2(1)=24.28$, $p<0.001$). There was a marginal interaction between AoA and LoE (β =0.003, SE=0, $\chi^2(1)=3.08$, $p=0.079$). There was also a significant interaction between AoA and rule ($\chi^2(1)=61.78$, $p<0.001$). Finally, there was a three-way interaction between AoA, LoE and rule ($\chi^2(1)=13.56$, $p=0.0088$). This analysis demonstrates that participants with different

AoA and LoE show consistent differences between the rules that they are tested on (e.g., judgments of past tense rule items were consistently better than judgments of determiner rule items). When this rule-related variability was factored out, then LoE showed a significant positive effect, where more years of input led to better knowledge of the grammar of English. Thus, the weak nature of LoE effects in previous studies could be due to the fact that earlier analyses treated rule variation as unexplained variance. The variation due to rule can be clearly seen in Figure 1b, where we split AoA into early learners (<12 years) and late learners (>12 years, both 120 participants). We used 12 years, because this is where a non-linearity occurs in the data (Flege et al., 1999), but we make no claim about the special role of this particular age.

The above analysis suggests that there are consistent differences among the rules, but since rule is a factor, each level of rule is treated as an arbitrary category and the analysis provides no explanation for these rule differences. One possible explanation of these rule differences is that participants rely on the knowledge of the raw frequency of the categories at the critical point in the test utterances. For example, knowing how frequently a verb is followed by a preposition can help to identify the error in the PAR rule item *The horse <u>jumped</u> the fence over yesterday*. To test this hypothesis, we tested a fully crossed model with categorical rule replaced by centered frequency for the adjacent categories at the critical point. The maximal model that converged contained random slope of AoA for test sentence and no slopes for participant. There was a significant negative effect of AoA (β = -0.2, SE = 0.02, $\chi^2(1) = 68.8$, $p < .001$), a marginal effect of LoE (β = 0.05, SE = 0.02, $\chi^2(1) = 3.7$, $p = .055$) and a negative effect of frequency (β = - -0.00001, SE = 0.000003, $\chi^2(1) = 4.96$, $p < .0.03$). There was a marginal interaction between AoA and LoE (β = -

0.006, SE = 0.004, $\chi^2(1) = 2.99$, p = .08). There was also an interaction between AoA and frequency (β = -0.0000005, SE = -0.0000002, $\chi^2(1) = 6.29$, p = .012). Finally, there was a three-way interaction between AoA, LoE and frequency (β = -0.00000005, SE = 0.00000003, $\chi^2(1) = 3.84$, p = .05). This analysis suggests that the rule differences in judgment behavior can be explained by a frequency measure. But unlike the previous model with rule as a factor, this model found only a marginal effect of LoE. Furthermore, since raw frequency will vary with the frequency of the component categories and the size of the corpus, we will test whether forward CPs, which are less sensitive to these factors, can explain this rule variation.

The next model included forward rule CP fully crossed with AoA and LoE. Rule CPs are computed from the raw frequencies divided by the previous category and hence they can vary between 0 and 1 (regardless of the frequency of the corresponding categories or the corpus size). The maximal model that converged contained random slopes for rule CP for participants and random slopes for AoA for test sentence. There was a significant negative effect of AoA (β = -0.2, SE = 0.02, $\chi^2(1) = 68.8$, p < .001), a positive effect of LoE (β = 0.04, SE = 0.02, $\chi^2(1) = 4.17$, p = .04) and a negative effect of rule CP (β = - 21.3, SE = 3.76, $\chi^2(1) = 20.1$, p < .001). There was a significant interaction between AoA and LoE (β = -0.01, SE = 0.004, $\chi^2(1) = 4.94$, p = .03). There was also a marginal interaction between AoA and rule CP (β = -0.5, SE = 0.33, $\chi^2(1) = 3.37$, p = .07). Finally, there was a three-way interaction between AoA, LoE and rule CP (β = -0.1, SE = 0.04, $\chi^2(1) = 5.93$, p = .015). This shows that as AoA increased, the weakening effect of LoE affected higher CP rules more that lower CP rules.

One puzzle in the L2 literature is that years of studying an L2 do not seem to positively predict knowledge of the L2 (DeKeyser, 2000; DeKeyser et al., 2010; Johnson & Newport, 1989; Lee and Schachter, 1997; McDonald, 2000). We replicated this finding (non-significant LoE) in our first model without any rule-related predictors. Furthermore, a model that included raw frequency did not yield a significant effect of LoE suggesting that this predictor did not factor out rule variations sufficiently to be able to see effects of LoE. But when rule was added as a factor or as rule CP, we found a significant positive effect of LoE, where performance improved with more linguistic exposure. In addition, while all of the models exhibited a sensitive period effect (a reduction in grammatical knowledge with increased AoA), only the rule CP model exhibited a significant interaction of LoE and AoA, where late learners benefitted from the input less than early learners. We suggest that previous studies did not find positive effects of LoE or interactions of LoE with other factors, because they did not fully factor out variation between rules.

In addition to clarifying the effect of AoA and LoE, these rule-related predictors in the model suggested that there were consistent preferences across items and participants for particular rules. The raw frequency and rule CP models both suggest that these rule differences are due to a negative relationship with frequency. This conflicts with the theories of L1 and L2 learning which argue that higher frequency should lead to greater accuracy (N. Ellis, 2002; Ambridge, Kidd, Rowland, & Theakston, 2015) and this work will attempt to explain this effect. To better understand this negative effect, we need to determine which measure of frequency provides the best account of the data. One way to compare these models is with R^2, which is the variance explained by each model (Johnson, 2014; Nakagawa &

Schielzeth, 2013). The model without rule CP explained about 21% of the variance. The model with raw frequency explained an extra 4% ($R^2 = 0.25$) and the rule CP model explained about 9% more ($R^2 = 0.30$). Since the rule CP model explained the most variance and uses a measure of frequency that is less dependent on word and corpus properties, we will use rule CP as our proxy for frequency in L2 learning.

The rule CP model revealed a significant three-way interaction between AoA, LoE, and CPs. This indicates that the weaker effect of LoE in later AoA learners impacted higher CP rules more than lower CP rules. Specifically, Figure 1b shows that the high CP rules DET and PL have a strong positive LoE slope in early AoA learners, but the slope is smaller in late learners. However, the slopes of lower CP rules like PST and 3PS were less affected by AoA. This suggests that late AoA learners have trouble using the high frequency of higher CP rules to acquire them better.

In sum, our reanalysis of Flege et al.'s data suggested a complex set of mechanisms in L2 grammatical learning. These learners showed a sensitive period effect (negative effect of AoA). In support of frequency-based approaches (e.g., N. Ellis, 2002), we found that the amount of input (LoE) had a positive effect on L2 learning, but this was reduced in late learners. However, frequency-based approaches cannot explain the negative effect of rule CP, where frequent noun-based rules were associated with lower accuracy scores than less frequent verb-based rules. Since each of the 240 participants was tested on each rule, the difference in the rules cannot be easily attributed to between-participant differences in motivation, social factors, or biological factors. A likely cause of the rule differences is transfer from L1, since Korean does not have determiners and uses plural marking less than English. Support for the transfer account can be found in Ionin and Montrul (2010), who

found that Korean learners of English had more trouble learning the generic interpretation of English determiners compared to matched Spanish learners, and this is presumably because Spanish speakers could use determiners in their L1 to enhance their learning of English. However, the Korean learners also learned third person singular verbs fairly easily even though the Korean language does not mark this distinction, so it is not obvious what kind of transfer mechanism could explain the learning of this rule. One possible account of language transfer are connectionist learning mechanisms that can encode similarity structure using distributed representations (Twomey, Chang, & Ambridge, 2014). In the next section, we examine whether a connectionist model is able to explain the findings in our reanalysis.

A connectionist model of the acquisition of morphosyntactic rules in L2

In the present work, we developed a computational model of L2 language acquisition and sentence processing and used it to examine the results observed in our Flege et al. reanalysis. The model is based on the connectionist model of L1 learning and processing called the Dual-path model (Chang, 2002). The model has several features that are relevant for the application to this dataset. First of all, the model has been shown to be able to learn abstract English grammatical constraints like those that are tested in Flege et al.'s study (Chang, Dell, & Bock, 2006). Secondly, the model can learn typologically-different languages (Chang, Baumann, Pappert, & Fitz, 2015) and in particular, it has been shown to be able to learn and explain various Japanese phenomena (Chang, 2009), which is a verb-final case-marked language like Korean. Finally the model uses linguistic input to make small changes to its morphosyntactic knowledge within a limited capacity memory and this means that

the knowledge that it learns for different rules may compete with or support learning of new rules (Fitz, Chang, & Christansen, 2011; Twomey, Chang, & Ambridge, 2014).

To simulate the environment of L2 learning at different ages, we first trained the Dual-path model on Korean-like L1 input until it reached adult-like performance. The weights in the Korean model were saved after every 3,000 epochs (1,000 epochs represented one human year) and were used as the starting points for the models learning English as an L2. By varying the starting point, we simulated children who had different amounts of Korean knowledge before moving to an English-speaking environment at different ages (AoA). Since the same model weights are used to learn both languages, the model instantiates the idea that shared systems are used for both L1 and L2 languages (Hartsuiker & Pickering, 2008; Hartsuiker, Pickering, & Veltkamp, 2004; Schoonbaert, Hartsuiker, & Pickering, 2007). This shared system assumption combined with the model's learning mechanism is consistent with evidence for transfer between L1 and L2 in various tasks (e.g., structural priming; Chang, Dell, & Bock, 2006).

The Korean L1 and English L2 Input Environment for the Models

Both the Korean and English languages consisted of simple intransitive, transitive, and dative structure sentences. The languages were composed of 40 words: 8 animate nouns, 8 inanimate nouns, 6 transitive, 6 intransitive, and 6 dative verbs. The Korean language included function words/morphemes (particles) that denoted case (e.g. nominative *ka,* accusative *ul,* dative *ey key*) and verb endings (e.g., *-da*). The English language contained morphemes to mark tense *(-ed, -ing*), 3rd person singular verb inflection (*-ss*), noun number (*-z*, this letter was chosen to

differentiate it from 3rd person singular inflection), and determiners (*a, an, the, this, that, two, three, many, several*) with the appropriate plural counterparts. To test particle movement rules, the grammar also contained two prepositions for creating phrasal verbs *(-down, -up*).

To train the models, sentences were paired with corresponding messages. Intransitive sentences had one argument Y in the message that mapped onto the subject slot. Transitives had an agent X and a patient Y argument that mapped onto the subject and object slots respectively. Finally, datives had an agent X, a patient Y and a goal Z argument that mapped onto the subject, object and indirect object slots (Table 5). Each argument was made up of a concept (e.g., CAT) and features that helped to structure the noun phrase (e.g. Y=CAT, THREE,DIST). There was a special argument for lexical action information (e.g., A=DANCE). In addition, the message contained event-semantics (e.g., E=PROG,YY), which had information about tense and aspect of the event. There were two possible tenses (present, PAST) with two possible aspects (simple, PROGressive). Present tense and simple aspect were considered default and had no event-semantic features. The event-semantics also contained features that encoded the number of roles that were required to describe a given event (XX, YY, ZZ). Both Korean and English languages shared the same meaning system but used different words in the lexicon to express the message. For simplicity, the Korean content word vocabulary was created by adding the letter ‘k’ to the beginning of the English content words (the labels play no role in the model’s behavior).

Table 5: *Examples of sentence structures used to train the model and the message that denoted the role of each constituent in the sentence*.

Structure	English/Korean Sentences	Message
Intransitive	*those cat -z are dance -ing*	A=DANCE
	kthat kcat ka ksit -iss -da	Y=CAT, THREE, DIST
		E=PROG, YY
Transitive	*the cat was carrying -ing this*	A=CARRY
	apple	X=CAT
	kcat ka kthis kapple ul kcarry -	Y=APPLE, PROX
	iss –eoss -da	E=PAST, PROG, XX, YY
Dative	*an elk give -ss sugar to the cat*	A=GIVE
	kelk ka kcat eykey ksugar ul	X=ELK, INDEF
	kgive –da	Y=SUGAR, PLUR, PROX
		Z=CAT
		E=XX, YY, ZZ

The language had features that captured some of the constraints in different rules in English and Korean (Table 6). Each noun argument in the message had a *kind* feature and a *number* feature that helped create noun phrases. The kind feature could be DEFinite, INDEFinite, PROXimate, or DISTal. The number feature could be SINGular, TWO, THREE, PLURal. All kind features were equally frequent and the singular feature was eight times more frequent than other number features. If the argument had PLUR number feature, then the noun was followed by *–z* (plural morpheme). PLUR nouns were preceded by the word *those* if the kind feature was DIST, the word *these* if the kind feature was PROX, the number word (e.g., *two*) if

the kind feature was DEF, the word *the* if the number feature was PLUR, and nothing if the kind feature was INDEF. If the number feature was SING, then DEF mapped to the word *the*, INDEF mapped to the word *a*, PROX mapped to the word *this*, and DIST mapped to the word *that*. If the kind feature was INDEF, then the TWO number feature mapped to the word *several* and the THREE number feature mapped to the word *many* (otherwise TWO mapped to the word *two* and THREE mapped to the word *three*). If the kind feature was INDEF and number was SING and the following noun started with a vowel, then the article *a* was changed to the word *an*. If the noun was a liquid or mass noun like *sugar*, *milk*, *water*, or *coffee* in the plural form, then the article was omitted. In the Korean language, there were no articles except for *kthis* and *kthat*, which were signaled by the PROX and DIST features. Number features like TWO mapped to *ktwo* and THREE mapped to *kthree* in pre-nominal position, but there was no other plural marking. The complex nature of English noun phrase rules is one possible reason that Korean learners of English have trouble judging the grammaticality of DET and PL rules.

There were also rules for verb construction that depended on the event-semantic features. If the features had PROG, then the verb was followed by *–ing* and preceded by the word *is* if the feature PRES was active or the word *was* if the feature PAST was active. If the aspect was simple, then *–ed* was added after the verb for the PAST feature or *–ss* for the PRES feature. If the subject was plural, then the word *is* was changed to the word *are*, the word *was* was changed to the word *were*, and the *–ss* marking was removed. In Korean, simple PRES verbs were followed by *–da*, simple PAST verbs by *–eoss –da*, PROG PRES verbs by *–iss –da*, and PROG PAST verbs by *–iss –eoss -da*. In English, there were several phrasal verbs. There were intransitive verbs *give-up* and *show-up* that combined dative verbs *give* and *show*

with the prepositions *up*. There were two transitive verbs *turn-down* and *break-down* that combined intransitive verbs *turn* and *break* with the preposition *down*. In Korean, these phrasal verbs were treated as separate verb forms. Therefore, the Korean model will have to learn that in English, verbs like *turn* can have two forms with different syntactic constraints and this should complicate the learning of the PAR rule. Although English and Korean have different rules for verbs, they are less different from each other in this respect.

Table 6*: Language constraints in English and Korean*

Relevant Rule	Relevant Message Features	English	Korean
DET, PL	X=DOG, DEF, SING	*the dog*	*kdog*
DET, PL	X=DOG, INDEF, SING	*a dog*	*kdog*
DET, PL	X=DOG, PROXIMATE, SING	*this dog*	*kthis kdog*
DET, PL	X=DOG, DISTAL, SING	*that dog*	*kthat kdog*
DET, PL	X=DOG, DEF, TWO	*two dog –z*	*ktwo kdog*
DET, PL	X=DOG, INDEF, TWO	*several dog –z*	*ktwo kdog*
DET, PL	X=DOG, INDEF, THREE	*many dog –z*	*kthree kdog*
DET, PL	X=DOG, PROXIMATE, TWO	*these dog –z*	*kthis kdog*
DET, PL	X=DOG, DISTAL, THREE	*those dog –z*	*kthat kdog*

DET, PL	X=DOG, DEF, PLUR	*the dog -z*	*kdog*
DET, PL	X=DOG, INDEF, PLUR	*dog –z*	*kdog*
DET, PL	X=DOG, PROXIMATE, PLUR	*these dog -z*	*kthis kdog*
DET, PL	X=DOG, DISTAL, PLUR	*those dog -z*	*kthat kdog*
PAR	A=TURNDOWN E=PAST, SIMP	*turn –ed down*	*kturndown –eoss –da*
3PS	A=TURN E=PRES, SIMP	*turn -ss*	*kturn -da*
PST	A=TURN E=PAST, SIMP	*turn -ed*	*kturn –eoss -da*
	A=TURN E=PRES, PROG	*is turn -ing*	*kturn –iss -da*
	A=TURN E=PRES, PROG	*was turn -ing*	*kturn –iss –eoss -da*

The grammar was created to match the order in which the 5 rules occurred in the corpora analysis in terms of their CPs (Table 7). The CPs for these rules in the model's training set were extracted using the same formula as in the corpus analysis. Since the language was a simplified version of English, the model input CP values only match the relative order of CPs in the human data (correlation between the two is .95).

Table 7*: Rule CPs in English corpora and in the grammar of the model*

Rule	Corpora rule CP	Model rule CP
DET	0.126	0.47
PL	0.125	0.4
PAR	0.085	0.22
3PS	0.05	0.16
PST	0.018	0.11

To train the models, 10 randomly generated training sets of 20,000 message-sentence pairs were created for each age of L2 acquisition. This created 10 model subjects for each different AoA group. The message was excluded from 25% of the training pairs to increase the syntactic nature of the learned representations.

Dual-path architecture

The Dual-path architecture is a connectionist architecture that can learn abstract rule-like syntactic representations that interact with messages in sentence production (Chang, 2002). It has two pathways; sequencing pathway for learning sentence structure (lower half of Fig. 2) and meaning pathway for learning word to

role mappings (upper half of Fig. 2). To adapt the model for L2 learning, the input and output layers have word units for the words in both English and Korean languages. Otherwise, the other features of the model are similar to the previous L1 versions of the Dual-path model.

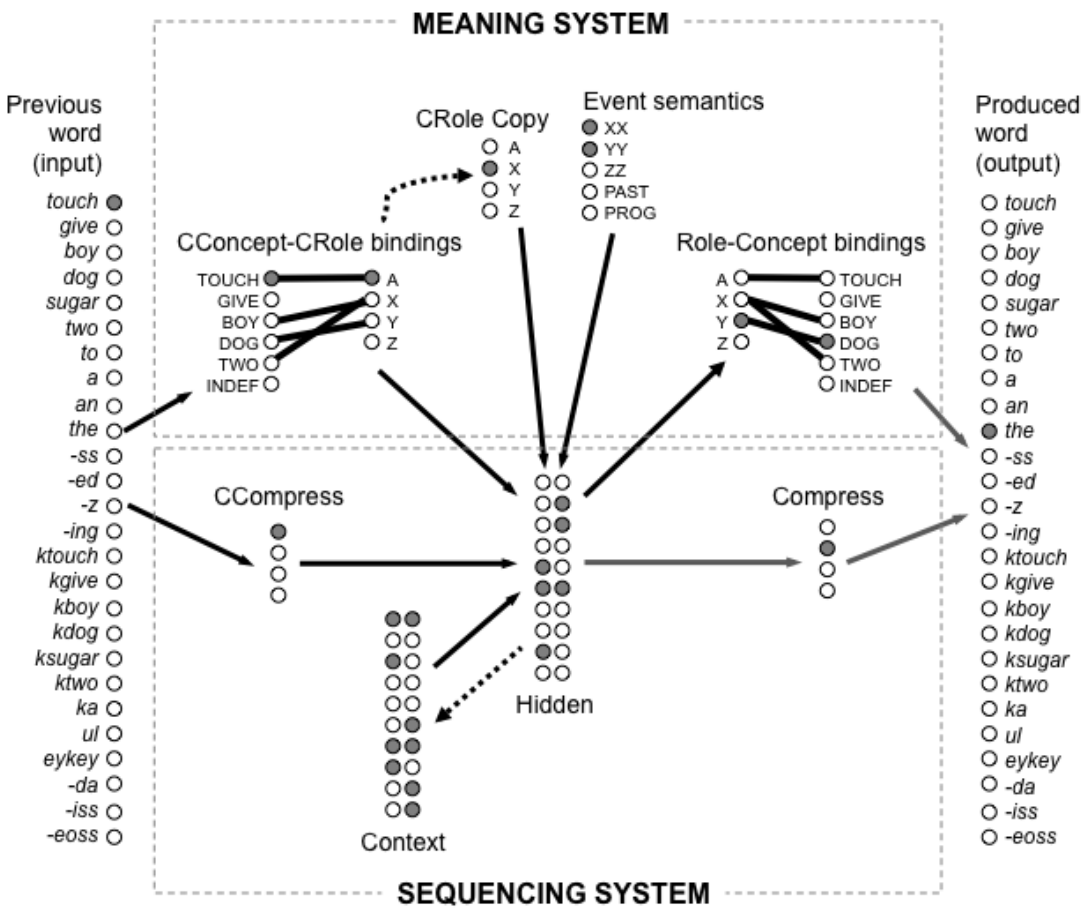


Figure 2. Dual-path Architecture. Black/grey arrows represent connections that have to be learned via back-propagation of error. Thick lines represent fast-changing message weights. Dotted arrows show copy links.

The sequencing pathway is based on a simple recurrent network (SRN) architecture (Elman, 1993). The network attempts to predict the next word in a sequence from the previously heard word. The previous word is an activation pattern in the Previous Word (Input) layer. Activation spreads from the Previous Word layer to the Hidden layer via a CCompress layer and then from the Hidden layer to the

Produced Word layer via another Compress layer. The function of the two compress layers is to force the model to form grammatical categories instead of learning individual word-to-word mapping (Elman, 1993). The Hidden layer learns and stores representations (activation patterns) that maps between the categories of the previous word and the next word and it also receives input from a Context layer that holds a copy of the Hidden layer's activation at the previous time step (dotted arrows in Figure 2). This allows the model to learn longer distance dependencies between elements (Christiansen & Chater, 1999b).

The model learns through back-propagation of error (Rumelhart, Hinton, & Williams, 1986). At the beginning of the training, the weights are initialized randomly with a range of 0.5. First, activation spreads through the network and generates a prediction about the next word in a sentence. The mismatch between the predicted Produced Word activations and the target is called *error*, and it is used to make small changes in the connection weights that generated the prediction. This error signal is then propagated back through the network adjusting the connection weights between all layers so that the predicted output better matches the target. Using such mechanisms, the model learns weights that encode the structure of the language (all solid arrows in Figure 2).

The sequencing system interacts with the message information in the meaning system. The message is instantiated in weights between a set of Role units and the Concept layer (Role-Concept bindings). When the message contains Y=DOG, the Y role unit is linked to the concept DOG with a weight of 6 (thick black lines in Figure 2). Since the Concept layer is linked to the Produced Word layer, the model can learn to activate a particular word when the appropriate concept is activated (concept DOG would activate *kdog* in Korean and *dog* in English). To allow the sequencing

system to know which roles are present in the message, the Event Semantics layer has units that signal the number of roles. For example, if this layer had XX and YY units activated, that would signal to the sequencing system that it should activate the agent X Role unit after the first determiner (since English agents tend to occur early in sentences). In contrast, the Korean model would learn to activate the agent X role in sentence initial position and would also learn to activate the subject particle *ka* afterwards to mark its role. In addition, the meaning system has a comprehension message, which tells the model the role of the previous word in the sentence, which helps the model produce structural alternations (e.g., active/passive). This system maps the Previous Word layer to the CConcept layer, which is linked to the CRole layer with a reverse copy of the Role-Concept links (thick black lines on left side of Figure 2). There is also a CRole Copy layer that helps the model keep track of the roles that have been processed.

In the present work, we apply the Dual-path model to explain L2 behavioral data in the Korean L2 English learners in the Flege et al. study. In the present work, we train models using Korean language as an L1 and then expose them to English as an L2. Consistently with the claim that L1 and L2 involved the same learning mechanism, but differ in the nature and timing of the input, we have kept the L2 version of the Dual-path model as similar as possible in its architecture and parameters to L1 English versions of the model (e.g., Twomey et al. 2014).

Evaluating the model's English grammatical knowledge

To gauge the overall learning of the language at different AoAs in the ten models, we assessed the word prediction accuracy every 3,000 epochs using 200 randomly generated test sentences. To see how successfully the model learned the

grammatical constraints in the rules in the Flege et al. study, we also examined its ability to distinguish grammatical and ungrammatical versions of the 5 rules in our reanalysis (DET, PL, PAR, 3PS, PST). Each test item had a matched grammatical and ungrammatical version (Table 8) and there were 100 items for each of the 5 rules.

Table 8*: Grammatical and ungrammatical sentences used to test models' performance with different rules*

Rule	Error Type	Example
DET	Grammatical	*A boy touch –ed the apple*
	Determiner omission	*A boy touch –ed __ apple*
PL	Grammatical	*Two boy –z touch -ed the apple*
	-z morpheme omission	*Two boy __ touch -ed the apple*
PAR	Grammatical	*A boy break -ss down the apple*
	Particle omission	*A boy break –ss __ the apple*
3PS	Grammatical	*A boy touch –ss the apple*
	-ss morpheme omission	*A boy touch __ the apple*
PST	Grammatical	*A boy touch –ed the apple*
	-ed morpheme omission	*A boy touch __ the apple*

To test the model's knowledge of each rule, sum of squares prediction error (the difference between the actual activation and the target activation for the word layer) for the target word at the part of the sentence where the grammatical and ungrammatical sentences differed was computed for both versions. For example, to test DET rule in the sentence *a boy touch –ed the apple*, the error of predicting the article *the* was compared to the error of predicting the word *apple* when the article

was omitted as in *a boy touch –ed apple*. For each rule, the average sum of squares error (SSE) was calculated for both the grammatical and ungrammatical items. Then a rule proportion measure was computed by dividing the average SSE of ungrammatical sentences by the sum of the average SSEs for both grammatical and ungrammatical sentences. Since error levels should be larger for ungrammatical sentences than grammatical sentences, higher rule proportion scores express better rule knowledge. If the model has not developed strong expectations about whether the verbs tend to be followed by determiners or not, then SSEs for both should be similar and rule proportion should be close to 0.5. Rule proportion in the simulations approximated the grammatical judgment accuracy measure in the Flege et al.'s study and our goal is to see if the model shows similar results to those observed in the reanalysis of their data. It is known that in ERP studies (e.g., Weber-Fox & Neville, 1996), the brains of L2 learners generate mismatch signals and this means that there is evidence that implicit prediction error signals like SSE are generated in their brains and could be used to make grammaticality judgments. However, since L2 tasks vary in their dependence on implicit and explicit knowledge (R. Ellis, 2004, 2005, 2006), different tasks might have different assumptions about the way that implicit signals like SSE are used to make behavioral choices.

Model simulations

We present several different simulations that attempt to approximate the L2 results in the Flege et al.'s reanalysis. Our first simulation tested whether the model's activation function could create the age-dependent sensitive period. The second simulation manipulated the sensitive period by reducing the model's learning rate after puberty. The third simulation introduced different learning rates for the lexical

and syntactic parts of the model. Finally, the fourth simulation implemented a model that received both English and Korean input to mimic the learning environment of most L2 learners.

Simulation 1: Activation function-based sensitive period effects

The activation function that is typically used in back-propagation has been argued to create sensitive period effects (Elman, 1993; A. Ellis & Lambon Ralph, 2000; Marchman, 1993; Mermillod, Bonin, Méot, Ferrand, & Paindavoine, 2012; Munakata & McClelland, 2003; Zevin & Seidenberg, 2002). In these models, activation is spread forward in the network and the net input for a unit is the weighted sum of input activations. The net activation is passed through a logistic/sigmoid activation function to create the output activation. For example, when the weighted sum input is 0, the logistic output activation will be 0.5. On the backward pass, the output activation is compared to the target to compute the error and this error is back-propagated through the network to change the weights. The first step of this back-propagation involves the computation of the derivative of the activation function. For the logistic activation function, the derivative is highest when the output activation is near 0.5 (derivative = o (1 - o) when *o* is the output activation). The derivative of the activation function modulates the effect of error so that the same amount of error will have a larger effect on the weights when the weighted sum input is close to 0. When the weights are small, the weighted sum input to a unit will be small and the large derivative will allow relatively large weight changes. Typically weights in these models are initialized to small values early on and hence these models should be more sensitive to input early in development compared to later in the development. Knowledge learned early in L2 learning can therefore become

entrenched and can inhibit later L2 learning (e.g. A. Ellis & Lambon Ralph, 2000; N. Ellis, 2013; Monner, Vatz, Morini, Hwang, & DeKeyser, 2013).

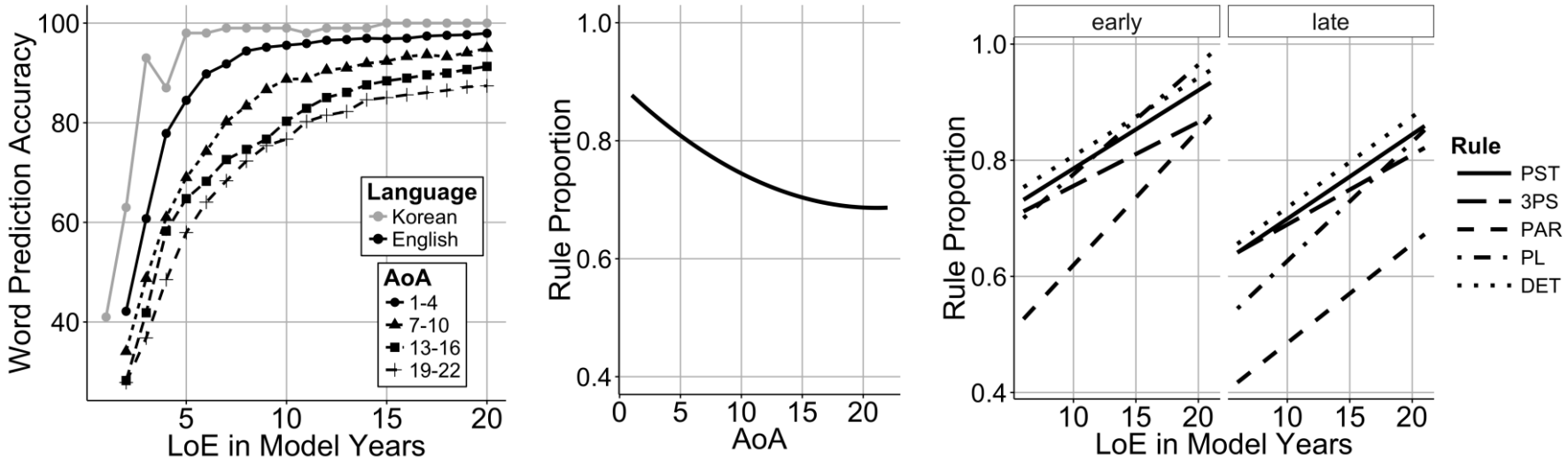
In previous versions of the Dual-path model (Chang, 2002), the output layer used a soft-max activation function, which creates a winner-take-all bias, so that the model prefers to select only one word. To test whether the logistic activation function can create a human-like L2 sensitive period, the first simulation used this activation function for the output layer and a constant learning rate throughout the training. To aid the comparisons with the human data, the model's age was represented as the number of training trials divided by 1000 (e.g. 1 model year refers to 1000 training trials or epochs). We applied a learning rate of 0.1 since this level allowed the model to learn Korean to an adult level within 5 model years.

Results

To examine the AoA effects, we looked at the overall word accuracy of the Korean models that started learning English at different AoAs. Fig. 3a shows the percentage of correctly predicted words in the Korean (grey line) and English (black lines) models that started learning the L2 at different ages. Later AoA models appeared to learn English slower, but reached similar accuracy levels after 20 model years.

To explore the model's grammatical knowledge with different rules over development, a mixed effect model was used to predict rule proportion scores with AoA, LoE, and rule CP fully crossed (Fig. 3c). All simulations contained model subject as a random intercept with random slopes for LoE crossed with Rule CP. The analysis revealed a negative effect of AoA (Fig. 3b), confirming that later AoA models performed worse than early AoA models (β = -0.01, SE = 0.001, $\chi^2(1)$ =

65.8, $p < .001$). LoE effect showed that longer exposure to language resulted in better overall scores ($\beta = 0.02$, SE = 0.001, $\chi^2(1) = 73$, $p < .001$). There was a positive main effect of rule CP showing that the models performed better with the higher probability rules ($\beta = 0.14$, SE = 0.01, $\chi^2(1) = 73.2$, $p < .001$). There was a two-way interaction between LoE and rule CP, where higher probability rule benefited more from increasing LoE ($\beta = 0.008$, SE = 0.002, $\chi^2(1) = 16.6$, $p < .001$). Finally, a three-way interaction between AoA, LoE and rule CP showed that this effect became stronger as AoA increased ($\beta = 0.001$, SE = 0.0003, $\chi^2(1) = 4.07$, $p = .04$).



(a) (b) (c)

Figure 3. (a) Word prediction accuracy of the Korean model (grey line) and English models that started learning English at different AoA (black lines). (b) Model rule proportion accuracy by AoA; (c) Model rule proportion by AoA, LoE, and Rule.

In sum, Simulation 1 showed a negative effect of AoA and this is consistent with connectionist models where the logistic function creates an age-dependent reduction in learning ability (A. Ellis & Lambon Ralph, 2000; Zevin & Seidenberg, 2002). However, the results of this model are different from those in Flege et al.'s (1999) data in several important ways (compare Fig 1a vs. Fig 3b). The sensitive period created by the logistic function is smaller than the one in human learners. Connectionist models learn from the input and therefore there is large LoE effect in the model. But late AoA human learners in Flege et al.'s data also showed lower sensitivity to LoE (Fig 1b), but the present model shows no interaction between LoE and AoA (Fig 3c). Furthermore, the human results showed a negative effect of rule CP, whereas the present model shows a positive effect. Finally, there is evidence that the sensitive period limits ultimate language attainment even with extensive input (DeKeyser & Larson-Hall, 2005) but the present model is able to catch up with early learners and hence does not match this aspect of human learning. For example, one of the participants in Flege et al. study scored only 58% judging the grammaticality of PL rule use even after 25 years of English input (model is closer to 90% at 20 model years). So while the logistic function can create age-dependent changes in learning, it does not capture the full behavior of L2 learners.

Simulation 2: Stretched Z Learning Rate Function for the Sensitive Period

Simulation 1 showed that activation function was not sufficient to create a human-like sensitive period. To make the effects stronger, we directly changed the model's learning rate as it aged. There is evidence that the sensitive period has a stretched Z function (Birdsong, 2005; Flege et al., 1999; Granena & Long, 2013; Johnson & Newport, 1989; Mayberry & Eichen, 1991), where performance is high

initially, but then declines gradually and is followed by a period of slower learning. These developmental changes were incorporated into the model by keeping the learning rate high (0.1) until model year 10, after which, the learning rate dropped to 0.025 over the following 6 model years (Fig. 4). With this learning rate function, later learners will have a lower learning rate in development and that might keep them from changing their Korean representations to the extent that would allow them predict English sentences with high accuracy.

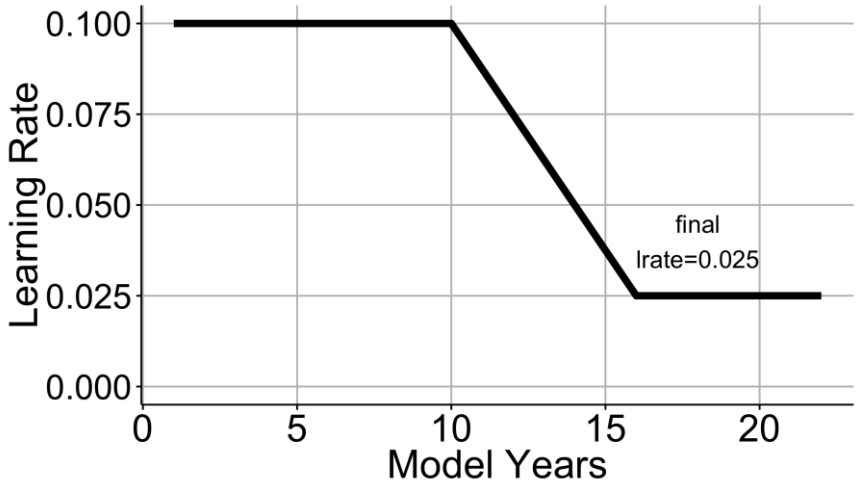


Figure 4. Learning rate as a function of model years

Also, since the previous L1 work with the Dual-path model used the soft-max function on the output layer (Chang, 2002), the following simulations will use that activation function to increase the similarity between the model's account of L1 and L2 learning.

Results

Fig. 5a shows the percentage of correctly predicted words in Korean (grey line) and English (black lines) models that started learning L2 at a different age.

While all models reached high scores with enough training, the speed with which they achieved it was slower in later AoA models.

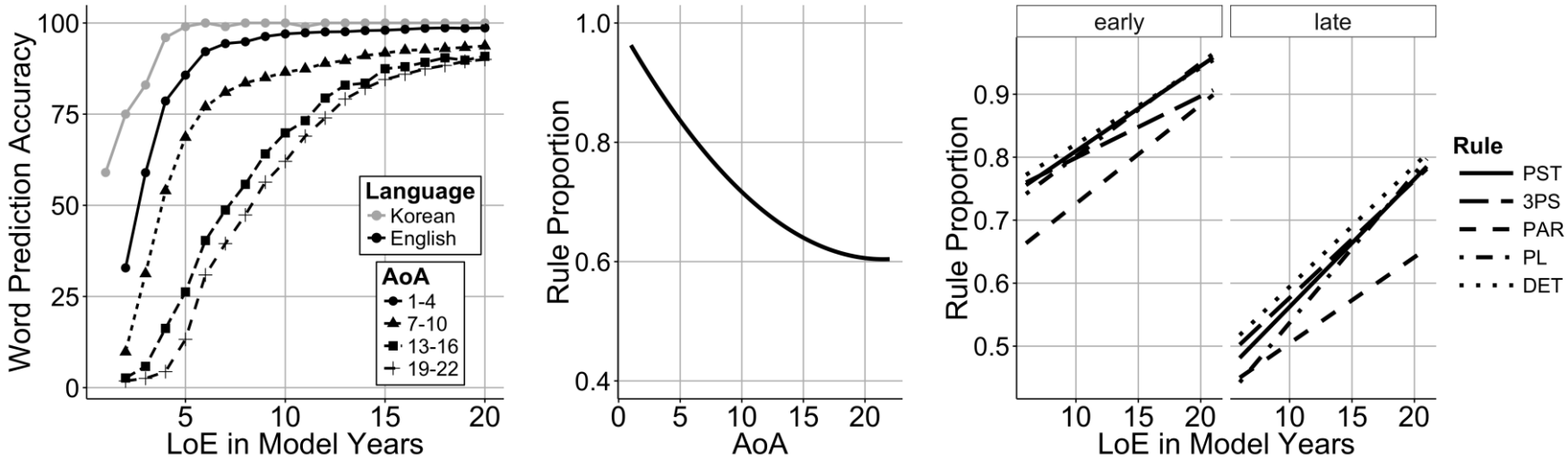


Figure 5. (a) Word prediction accuracy of the Korean model (grey line) and English models that started learning English at different AoA (black lines). (b) Model rule proportion accuracy by AoA; (c) Model rule proportion by AoA, LoE, and Rule.

Statistical analysis confirmed that there was a significant negative effect of AoA (Fig. 5b), indicating that later AoA models had greater difficulty in distinguishing grammaticality (β = -0.02, SE = 0.001, $\chi^2(1) = 94.4$, $p < .001$). There was a positive effect of LoE (β = 0.01, SE = 0.001, $\chi^2(1) = 101$, $p < .001$), which showed that language exposure increased the models' accuracy, and a positive effect of rule CP (β = 0.07, SE = 0.007, $\chi^2(1) = 51.6$, $p < .001$), which demonstrated that they performed better with higher CP rules (Fig. 5c). There was a positive two-way interaction between AoA and LoE, showing that later AoA models benefited from increasing LoE more that early AoA models (β = 0.0005, SE = 0.0001, $\chi^2(1) = 11.6$, $p < .001$). There was also a positive interaction between LoE and rule CP, showing higher CP rules were more sensitive to increasing LoE than lower CP rules (β = 0.005, SE = 0.0001, $\chi^2(1) = 20.3$, $p < .001$). Finally, a three way interaction between AoA, LoE and rule CP showed that this effect became stronger as AoA increased (β = 0.0005, SE = 0.0001, $\chi^2(1) = 11.9$, $p < .001$).

The reduction in the learning rate created a stronger sensitive period effect that resembles the human data more closely (compare Fig. 1a and 5b). However, like Simulation 1, the late learning models acquired the language to near native levels (Fig 5a) and the effects of rule CP and the interaction between LoE and AoA were in the opposite direction to the corresponding effects in the human data.

Simulation 3: Lexical and syntactic learning rates

Cognitive and neurobiological explanations of sensitive period often focus on differences between lexical and syntactic learning (Paradis, 2004, Ullman, 2015).

This distinction is supported by the studies of feral children like Genie, who started learning her first language at 13 and was able to learn new words faster than other children in the same MLU stage of development, but never fully mastered English grammatical knowledge (Curtiss, Fromkin, Krashen, Rigler, & Rigler, 1974; Curtiss, Fromkin, Rigler, Rigler, & Krashen, 1975; Fromkin, Krashen, Curtiss, Rigler, & Rigler, 1974). In addition, Singleton & Lengyel (1995) have argued that there is no sensitive period for vocabulary learning in either L1 or L2 language and in some cases, L2 learners outperform native learners in word learning tasks (Kaushanskaya & Marian, 2009). There is also evidence that late learners show N400 signatures for newly learned L2 words even after only 14 hours of instruction (McLaughlin, Osterhout, & Kim, 2004). Weber-Fox and Neville (1996) found reduced syntactic P600 effects in late learners (AoA > 11) for phrase structure, but lexical N400 effects were present for both early and late learner when a word appeared in a position that was not expected in terms of meaning. These studies suggest that AoA has a greater negative impact on syntactic learning than lexical learning.

To examine this hypothesis in the model, we incorporated separate learning rates and varied them independently for the lexical and syntactic learning weights in the model. The lexical learning system included the connections between Concept and Produced Word layers and the connections between Hidden, Compress, and Produced Word layers (grey arrows in Fig. 2). These parts of the model were responsible for selecting the right output word while the remaining parts of the model were involved in learning structural regularities (black arrows in Fig. 2). The syntactic learning rate remained fixed at 0.1 for the first 10 model years and then was reduced to 0 across the following 6 years. The learning rate in the lexical learning part of the system remained fixed at 0.1 throughout training (Fig. 6).

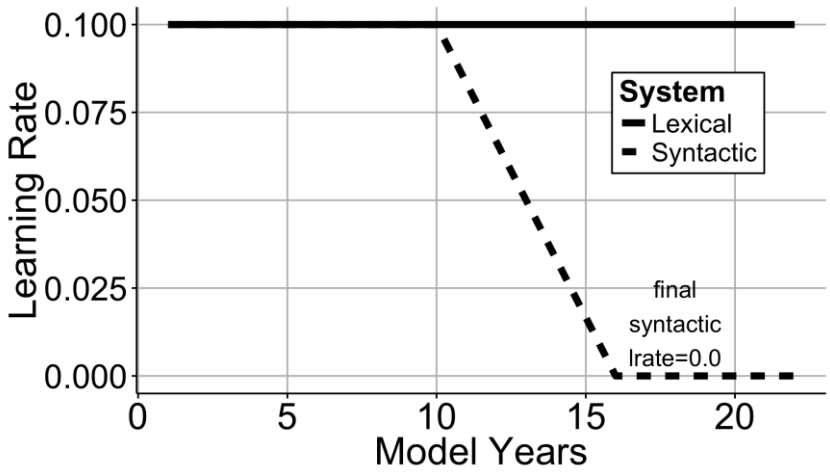


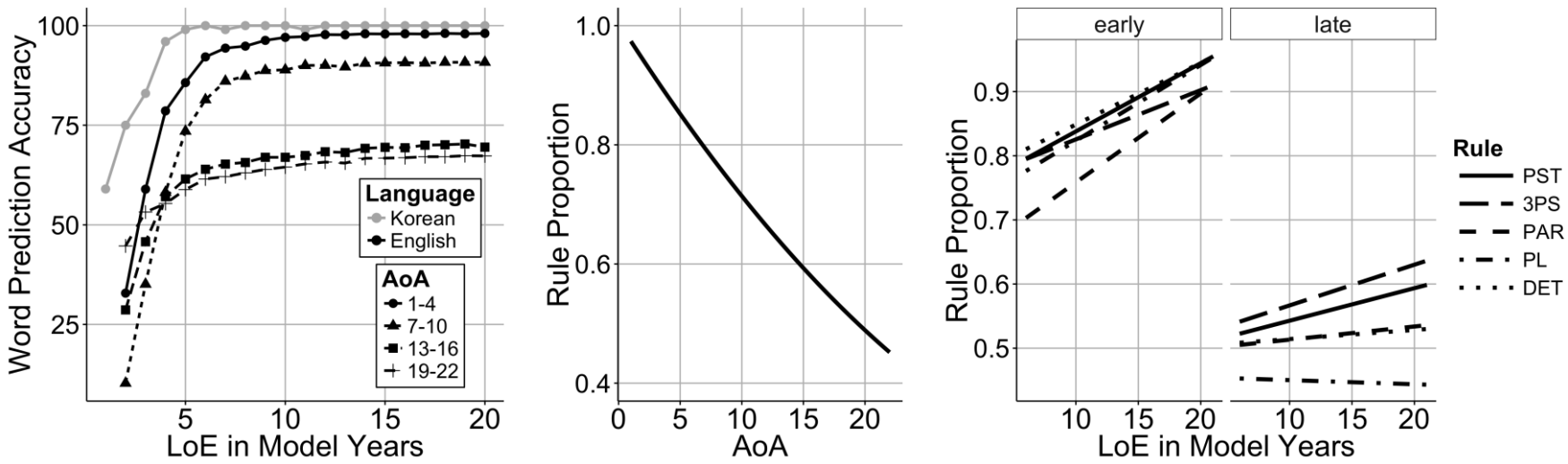
Figure 6. Learning rate as a function model's age in years for lexical and syntactic systems

The focus on the distinct properties of the lexical and syntactic systems is similar to Ullman's (2001) declarative/procedural theory. In his theory, syntactic rule learning depends on implicit procedural learning and this is in agreement with our model, which only implements implicit statistical learning (Chang, Janciauskas & Fitz, 2012). However, Ullman's theory argues that lexical learning involves declarative systems. In our model, long-term lexical knowledge is also learned though procedural learning. The fact that procedural learning is involved in lexical learning is supported by studies showing that word-based repetition priming is present in anterograde amnesic patients, even though their declarative learning systems are damaged (Gordon, 1988; Mayes & Gooding, 1989; Schacter & Graf, 1986). This type of priming has been argued to reflect implicit learning processes (Oppenheim, Dell & Schwartz, 2010). However, the higher learning rate for lexical learning in the present simulation could help to support fast learning of arbitrary associations and this is one of the features of declarative memory. Thus, while this simulation has similar assumptions to Ullman's account, the model does not fully implement the declarative components of his account.

Results

The learning rate changes in the structure learning system created a clear sensitive period effect, where later AoA models performed noticeably worse than early AoA models. However, the later AoA models were still able to use the lexical learning system to support their English grammatical knowledge and their accuracy levels approached 65% (Fig. 7a).

Analysis of rule learning revealed that there was a significant negative effect of AoA (Figure 7b, β = -0.02, SE = 0.001, $\chi^2(1) = 35.8$, $p < .001$), a positive effect of LoE (β = 0.004, SE = 0.001, $\chi^2(1) = 131$, $p < .001$) and a marginal negative effect of rule CP (β = -0.09, SE = 0.01, $\chi^2(1) = 3.1$, $p = .08$). There were also three negative interactions between AoA and LoE (β = -0.0006, SE = 0.0001, $\chi^2(1) = 4.87$, $p = .03$), AoA and rule CP (β = -0.02, SE = 0.001, $\chi^2(1) = 71.1$, $p < .001$), and LoE and rule CP (β = -0.007, SE = 0.001, $\chi^2(1) = 23.5$, $p < .001$). Finally, there was a three-way interaction between AoA, LoE and rule CP (Fig. 7c), showing that with increasing AoA, higher CP rules benefited from increasing LoE less than lower CP rules (β = -0.001, SE = 0.0001, $\chi^2(1) = 37.9$, $p < .001$).



(a) (b) (c)

Figure 7. (a) Word prediction accuracy of the Korean model (grey line) and English models that started learning English at different AoA (black lines). (b) Model rule proportion accuracy by AoA; (c) Model rule proportion by AoA, LoE, and Rule.

Separating lexical and syntactic learning parts of the system successfully captures the effects observed in the Flege et al. data. Importantly, it showed that the LoE effect was weaker in later AoA models (Fig 5c). Also, the direction of rule CP effect flipped from positive to negative. While the main effect of CP was marginal, it's interaction with AoA and especially the three-way interaction between AoA, LoE and rule CP matched the human results showing that with increasing AoA, higher CP rules benefitted from increasing LoE less than lower CP rules.

After 16 years, the model's syntactic learning rate goes to zero and therefore the late learning models are learning to predict English words using Korean syntactic knowledge. Figure 7a shows that 19-22 learners do acquire the ability to correctly predict English words with an accuracy of around 70%. This relates to ERP evidence showing that late L2 learners exhibit similar syntactic P600 effects as native L1 speakers in some conditions (Foucart & Frenck-Mestre, 2011; Sabourin et al., 2006). These effects are sometimes used to argue against critical period effects, since late learners are exhibiting similar patterns to native speakers. However, even though the late learning models do not have native-like L2 syntactic representations, their L1 representations are sufficient to create differences across L2 rules. This is especially the case when behavior across the whole network/brain is averaged into a single measure like Rule Proportion/ERPs, where it can appear as if human/model learners are processing L2 sentences in a native-like manner.

In this and the previous simulations, the models stopped receiving Korean language input once English was introduced as an L2. Although the complete suspension of L1 input is rare, there are many L2-dominant bilinguals (Flege, Mackay, & Piske, 2002), particularly those with early AoA with long LoE in strongly monolingual environments who would be well characterized by this model.

Furthermore, there are two populations which are similar to these models in that they show AoA effects even though they mainly receive input from one language: international adoptees and deaf learners of sign language. International adoptees are adopted into a new culture and exclusively get input from one language. Several studies have found that, while these learners have similar motivation and input to native learners, they acquire the language to a lower level than the equivalent native learners and language proficiency is negatively related to age of adoption (Gardell, 1979; Gauthier & Genesee, 2011; Hyltenstam, Bylund, Abrahamsson, & Park, 2009). Deaf learners of sign languages also show AoA effects, even though sign language is their L1 and they are motivated to learn it (Boudreault & Mayberry; 2006; Mayberry, 2010; Mayberry & Eichen, 1991). These AoA effects support (DeKeyser & Larson-Hall, 2009, p. 88) claim that the "age of acquisition keeps playing a large role when social and environmental variables are removed" and this suggests that some biological changes in learning ability may be involved in creating the sensitive period. Although the sensitive period is evident even when learning a single language, it is the case that most L2 learners continue to use the L1 after they start to receive L2 input and we examine whether this has an effect in simulation 4.

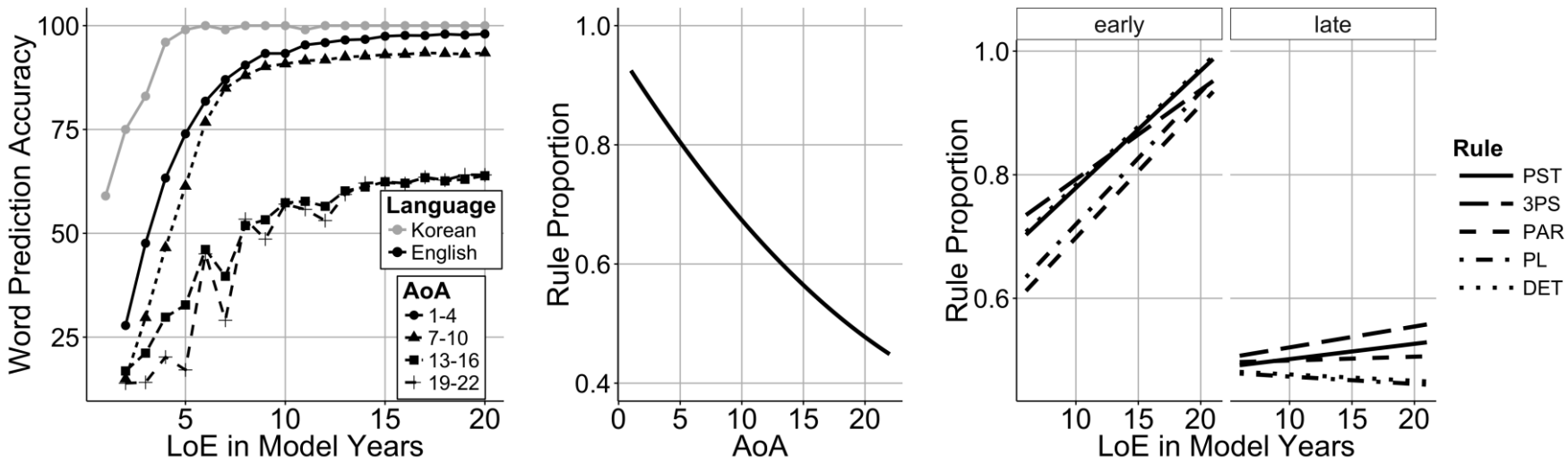
Simulation 4: Korean and English input in L2 learning

Our final simulation examines whether the results of previous analyses generalize to the environment where the models receive both English and Korean input. Initially, the model learned Korean as an L1 and then it was given half-English and half-Korean input interleaved in a random order (akin to balanced bilinguals). To signal the target language, an additional language feature was added to the event

semantics, which told the model which language it was producing. The syntactic and lexical learning rate parameters as well as other aspects of the simulation were identical to simulation 3.

Results

As in Simulation 3, late learning models did not achieve native-like language accuracy (Fig 8a). There was a negative main effect of AoA effect (Fig. 8b, β = -0.02, SE = 0.007, $\chi^2(1) = 27.5$, $p < .001$), a positive effect of LoE (β = 0.01, SE = 0.0004, $\chi^2(1) = 137.6$, $p < .001$), and a negative effect of rule CP (β = -0.08, SE = 0.007, $\chi^2(1) = 45.8$, $p < .001$). There was a negative interaction between AoA by LoE (β = -0.001, SE = 0.0001, $\chi^2(1) = 37.3$, $p < .001$), and a negative interaction between AoA and CP (β = -0.02, SE = 0.001, $\chi^2(1) = 28.6$, $p < .001$). There was also a marginal interaction between LoE by rule CP (β = -0.002, SE = 0.001, $\chi^2(1) = 3.24$, $p = .007$), Finally, there was a three-way interaction between AoA, LoE, and rule CP (Fig. 8c, β = -0.001, SE = 0.0001, $\chi^2(1) = 82.8$, $p < .001$).



(a) (b) (c)

Figure 8. (a) Word prediction accuracy of the Korean model (grey line) and English models that started learning English at different AoA (black lines). (b) Model rule proportion accuracy by AoA; (c) Model rule proportion by AoA, LoE, and Rule.

To better understand how bilingual input affected learning, we also examined the model's code switching behavior (e.g., producing Korean words in English sentences) in both simulations. Figure 9 shows the proportion of Korean words produced by the models that received English-only L2 training (Simulation 3) or English and Korean L2 training (Simulation 4). Late AoA models in Simulation 4 continued using many Korean words in English sentences even after a substantial number of years of English input. These results approximate the results of studies which have found that code-switching rate was higher (14%) in late learners than in early learners (6%; Sheng, Bedore, Peña, & Fiestas, 2013). Code-switching is very context dependent and this model does not fully capture all of the factors that influence code-switching. For example, Moore (2013) found that English-learning Japanese speakers often switched to their L1 while preparing for an English presentation and the percentage of L1 could vary greatly within the same speaker (e.g., 28% to 84%) depending on the proficiency of the interlocutor. Although AoA information was not provided for the learners in this study, there were some participants who used their L1 approximately 88% of the time, which approximates the high levels in late learners in Simulation 4.

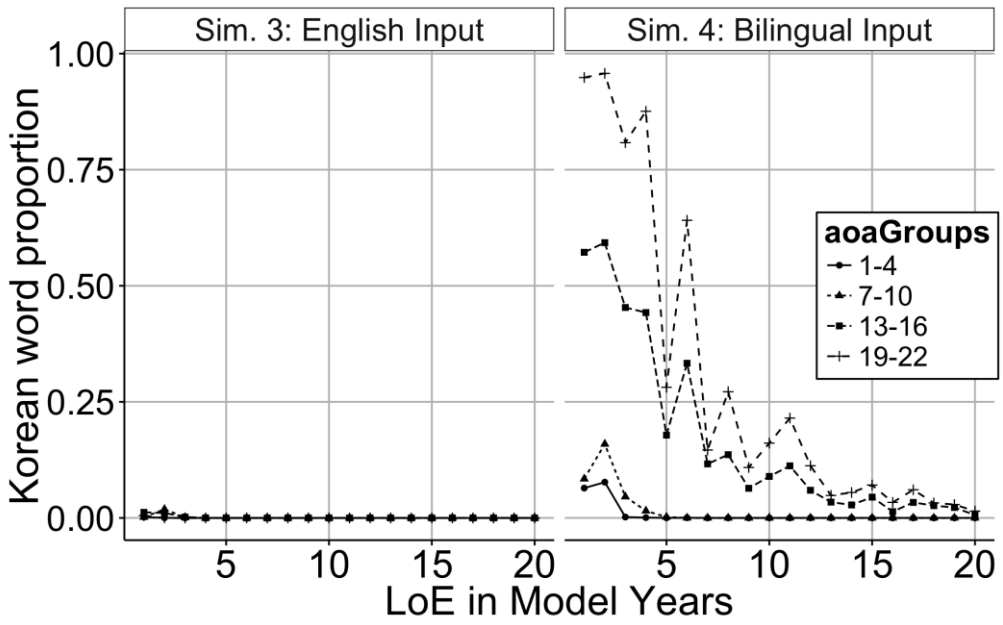


Figure 13. Proportion of L1 Korean words produced by English-only model and by Bilingual models at different AoAs over LoE

In contrast to the marginal effect of CP in Simulation 3, the bilingual input in this simulation created a significant negative effect of CP. This means that even though the input for DET/PL was higher in the model's input, the model learned these rules less well compared to less frequent rules like 3PS/PST. We will discuss the source of these effects in the discussion. Overall, this model provided a good match to the effects of AoA, LoE, and CP seen in the Flege et al.'s reanalysis. In addition, it provided some evidence for code-switching behavior within a model of sentence production that has learned both L1 and L2.

General discussion

This study of L2 learning examined the interaction between AoA and input factors like LoE and CP. In support of a critical/sensitive period, our reanalysis of Flege et al.'s (1999) data found a significant effect of AoA on L2 linguistic behaviors. Some studies have argued that entrenchment with connectionist activation

functions can explain sensitive period effects (A. Ellis & Lambon Ralph, 2000; Munakata & McClelland, 2003). Simulation 1 examined this and found that these mechanisms alone were not sufficient to explain all of the features of the sensitive period in the learning of grammatical knowledge. To simulate the sensitive period effects seen in humans, we changed the model's learning rates following a stretched Z function (Granena & Long, 2013). Our claim is that this learning rate is an age-dependent learning parameter that influences L1 and L2 learning equally (some L1 phenomena can also be explained with learning rate changes, e.g. Peter, Chang, Pine, Blything & Rowland, 2015). We can contrast this with the view that the critical period reflects specialized *linguistic* parameters, such as a head-direction parameter (e.g. Chomsky & Lasnik, 1993), which are set within the critical period. Instead, the use of general learning parameters here suggests that linguistic critical periods could be due to mechanisms that evolved originally for non-linguistic critical period phenomena (Knudsen, 2004; chick imprinting; Lorenz, 1937; birdsong; Marler, 1970; cochlear implants; Harrison, Gordon, & Mount, 2005).

The learning rate changes in the model may also have a role in social/motivational/input-based accounts of the sensitive period. For example, it could be the case that children receive more optimal input for language learning than adults. In order for this input to create sensitive period effects, the knowledge that is learned from early optimal input should not be overwritten by the sometimes more than 20 years of less optimal adult input. The model's stretched Z learning function is one way to ensure that early experiences due to various factors persist in spite of further learning. Thus, regardless if one believes in a purely biological account of the sensitive period, or in a social/motivational/input-based account, there needs to be an

age-dependent learning mechanism that insures that this early experience persists such that it can influence testing that takes place years later.

The main impetus for the present work was the finding that the amount of L2 input was a poor predictor of proficiency (DeKeyser, Alfi-Shabtay, & Ravid, 2010; DeKeyser, 2000; Johnson & Newport, 1989; Lee and Schachter, 1997; McDonald, 2000). Such findings are compounded by evidence suggesting that some L2 learners are better at recognizing the grammatical use of lower frequency rules like the third person singular than higher frequency rules like determiners (Johnson & Newport, 1989; Flege et al., 1999). To explain this we used corpus analyses to characterise the frequency of different rules (rule CP) and used this to factor out rule variation. When rule CP was added to the Flege et al.'s reanalysis, LoE went from non-significant to a significant positive effect, which suggests that the lack of LoE effects in some studies may be due to the fact that this effect was obscured by rule variation. LoE was also significant when rule was included as a factor, which demonstrates that this result does not depend on a particular approach to computing rule CPs.

We also found that late AoA learners were less sensitive to the input (LoE) than early AoA learners. Our simulation 2 showed that the stretched Z learning function was not sufficient to explain this interaction. To model this effect in simulation 3, we assigned separate learning rates to the lexical and syntactic parts of the system (Paradis, 2004; 2009; Ullman, 2001). The lexical part retained a high learning rate throughout the training, whilst the syntactic learning rate followed the stretched Z function. The early AoA models had a high syntactic learning rate, which allowed them to reconfigure their Korean syntactic representations into representations that were more appropriate for English. However, the later AoA models had a low syntactic learning rate and hence their high lexical learning rate

forced them to associate English words with sequence representations that were still partially Korean. On this account, the weaker effect of LoE in late AoA learners is due loss of syntactic learning ability in the late learners and their greater dependence on lexical learning as a result. This account is supported by ERP studies of L2 learners' brain activity that have found that syntactic components such as the P600 differ from native learners more than lexical-semantic components such as the N400 (e.g. Hahne, 2001; Hahne & Friederici, 2001; Weber-Fox & Neville, 1996) . Furthermore, recent studies have tested grammatical distinctions that yield P600 effects in native speakers and proficient L2 learners, but which yield N400 effects in some late AoA L2 learners (McLaughlin et al., 2010). Since the N400 is traditionally associated with lexical/semantic expectations, N400 effect for a grammatical distinction supports the claim that late AoA learners may be using lexical learning to a greater degree than early AoA learners to support their syntactic processing in the L2.

Although the syntactic learning rate in the model was completely switched off at age 16, this did not fully impair the model's ability to learn syntactic regularities and to differentiate between different rules. This is because the lexical and syntactic learning rates are both being used to learn word regularities that support syntactic grammaticality judgments (e.g., DET rule depends on predicting the word *the* after verbs). This means that the lexical and syntactic behaviors may not be transparently related to lexical and syntactic learning in human and model behavior (see the syntactic/lexical division of labor in Chang, 2002). For example, Granena and Long (2013) argued that lexical learning ability follows a similar negative learning function as syntactic learning, but their measure of lexical learning involves multi-word collocations, which in our model would be encoded in the sequencing system and

would be sensitive to the syntactic learning rate. We have shown here that lexical learning can be used to learn grammaticality constraints in a way that mimics the behavior in late L2 learners. Overall, our account predicts that under similar input conditions, early AoA learners can use their higher syntactic learning rate to learn deeper and more abstract syntactic rules than later AoA learners and support for this can be found in Hudson Kam and Newport (2005) study, which found that children were more likely than adults to regularize the artificial language that they were learning.

Although input is important for L2 learning, L2 learners appear to perform worse with higher frequency rules like determiners than lower frequency rules like 3rd person. There was a significant negative effect of rule CP in our reanalysis of Flege et al. (1999) study and similar effects have been found in other studies (DeKeyser, 2000; Johnson, 1992; McDonald, 2000; Murakami & Alexopoulou, 2015). Since the effect is negative, it is not straightforwardly explained by input-based theories (N. Ellis). A likely explanation is transfer/interference from the L1, but it is often hard to formalize the morphosyntactic similarity across languages. The fact that the model does not capture this negative relationship in simulation 1 and 2 suggests that the separate learning rates for lexical and syntactic knowledge in simulation 3 and 4 are important in capturing these effects. Low frequency rules like PST and 3PS were relatively simple and the late learning models were able to correctly predict English structures with Korean syntactic representation by using lexical learning to linking English words with these representations. The higher frequency DET/PL/PAR rules were more complex and harder to predict from Korean representations (these rules depend more on learned syntactic knowledge). What the model highlights is an implicit assumption of transfer accounts, which is that transfer from the L1 assumes

that the L2 syntax is learned slowly enough to make it preferable to link L2 words to L1 structures and this assumption is instantiated by a gradual reduction of the syntactic learning rate while lexical learning rate remained high. Although we do not know the exact nature of the L1/L2 similarity that determines transfer/interference between languages, the model provides an explicit implementation of a mechanism that captures some of these transfer effects and future work should examine the nature of this mechanism and its relation to equivalent transfer effects in human studies.

The models presented here are not fully realistic simulations of L2 learners. Rather, like the mixed model reanalysis, they provided a simplified representation of a complex pattern of data. It is also not the case that one simulation is the best simulation of all L2 speakers. It may be the case that early AoA learners and learners who have a long LoE are more likely to be exposed to exclusively L2 input as in Simulation 3 (L2-dominant bilinguals; Flege, MacKay, Piske, 2002), while late AoA learners and learners who have only a short LoE are more likely to maintain connections to their L1 as in Simulation 4 (balanced bilinguals). Furthermore, different results would arise if the same model was trained on different L1/L2 pairs (Murakami & Alexopoulou, 2015) and the present simulations do not explain variation in implicit and explicit aspects of L2 tasks (R. Ellis, 2005; see Chang, Janciauskas, & Fitz, 2012 for one extension of the Dual-path model for one explicit phenomena). The main purpose of these models is to offer a starting point for developing a computational account of L2 learning.

The main innovation in the present work is the demonstration that a model of L1 language acquisition and production can explain L2 performance over various AoA, LoE, and grammatical rules. The extension to L2 learning involved minor

changes in learning rates without any major architectural changes. Since the same network/mechanism is used for encoding L1 and L2 rules, the model predicts that there will be transfer between L1 and L2 structures (Foucart & Frenck-Mestre, 2012; Hartsuiker, Pickering, & Veltkamp, 2004; Ionin & Montrul, 2010; MacWhinney, 2005; Sabourin, Stowe, & de Haan, 2006) and similar brain areas/ERP signatures for L1 and L2 processing (Friederici, Steinhauer, & Pfeifer, 2002; Kotz, 2009). Learning rate variation in syntactic and lexical systems offers an account which allows the same learning mechanism and network to explain the large differences due to AoA. Overall, this approach provides an explicit account of the complex interactions of various aspects of L1 and L2 structure learning.

Appendix

The simulations were implemented using Version OSX-1.0a of the LENS connectionist software package (Rohde, 1999; Brouwer, de Kok & Fitz, 2013). Unless stated otherwise, default parameters of the simulator were used. Simulation is available at: https://sites.google.com/site/sentenceproductionmodel/Home/l2model.

The model had 109 units in the Previous Word/Produced Word layers, 20 units in the Compress/CCompress layers, 30 units in the Hidden/Context layers, 5 units in the Role/CRole/CRole Copy layers, 43 units in the Concept/CConcept layers, and 6 units in the Event Semantics layer. A Context layer held a copy of the activation of the Hidden layer and was reset to 0.5 at the start of an utterance. The Previous Word layer received one-to-one inputs from all of the Produced Word layer units and from the previous target inputs, and a winner-take-all filter was applied. Thus, during learning from the speech of others, the Previous Word was set to the heard target word. However, when the model was generating its own utterance, the

Previous Word layer was set to the word that model had previously produced.

The CRole layer had soft-max activation function. The CRole Copy layer (Fig. 2, top panel, centre) which averaged a copy of its own previous activation with the activation of the CRole layer. To help the model learn the links between the previous word and its appropriate concept (i.e., the weights between the Previous Word and CConcept layers, Fig. 2, far left), the previous activation of the Concept layer was used as a training signal for the CConcept layer. The Role-Concept links in the production message, the CConcept-CRole links in the comprehension message, and Event Semantics activations were all set before a training or test sentence was processed.

Unless specified otherwise, units in all layers used the sigmoidal logistic activation function, with activation values running between 0 and 1. The Produced Word layer used the logistic activation function in simulation 1 and soft-max in the other simulations. Weights were initially set to the values uniformly sampled between -0.5 and 0.5. Units were unbiased, unless specifically mentioned, in order to make the layers more dependent on their inputs for their behaviour. However, Concept units were biased to -3 to ensure that they had a low default activation level.

A version of back-propagation was used to train the model where derivatives were clipped at 1.0 (Doug's momentum; Rohde, 1999). Momentum was 0.9. Weights were updated after each message-sentence pair had been trained. Training began by randomising all weights (same model seed was used for all runs, but input generation used different seeds). At the start of each utterance, the message was set. After the sentence was generated, the sequence of Produced Word activations was processed by a decoder program that yielded the produced sentence. Sentences were

then processed by a syntactic coder program that added the syntactic and message tags. The model's output was compared with the target sentence and the sentence was considered accurate if the all the words were correctly produced.

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