**Words in the CLOUD: How orthographic similarity and bilingual experience facilitate
foreign vocabulary learning**

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Abstract

Learning a foreign language as an adult entails acquiring a large number of novel words or vocabulary. The literature highlights that orthographic similarity and bilingual experience independently facilitate foreign vocabulary acquisition. Here, we explored the combined effects of orthographic similarity and bilingual experience on foreign vocabulary learning using complementary behavioral and computational approaches. Study 1 compared Spanish monolingual, Spanish-English bilingual, and Spanish-Basque bilingual adult participants, who learned an artificial vocabulary comprised of nonwords with more or less orthographic similarity to Spanish. All groups found it easier to recognize and produce more similar than less similar words, while both bilingual groups outperformed the monolingual group in vocabulary learning, irrespective of orthographic similarity. In Study 2, we developed a neural network model that implemented a unified, distributed, and dynamic orthographic lexicon to explore how these effects could emerge from exposure to words in one or two languages. We pre-trained this architecture on monolingual or bilingual input, then tested the model's capacity to learn the novel words used in Study 1. The simulations reproduced the orthographic similarity effects and the overall advantage for experience with bilingual input observed in the behavioral results. The present study demonstrates that the seemingly disparate effects of orthographic similarity and bilingual experience can be explained by a common computational framework, in which distributed representations of orthographic word forms are stored in a unified space and dynamically modified by learning experience.

Keywords: vocabulary learning, bilingualism, computational modeling, Long Short-Term Memory, recurrent neural networks

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Learning a foreign language as an adult is a rewarding but challenging endeavor that entails accruing a massive vocabulary to achieve high proficiency. The Council of Europe estimates that proficient language learners must acquire around 10,000 base words (not counting inflections), including words not used in everyday conversations (Council of Europe, 2001). Since vocabulary acquisition is one of the most challenging aspects of foreign language learning, it is imperative to understand the factors that facilitate or hinder this process so as to maximize learning outcomes (Schmitt, 2019). This work leverages behavioral evidence and computational modeling to show that foreign vocabulary learning can be facilitated by orthographic similarity and bilingual experience. It also addresses two long-standing theoretical questions: (a) Does exposure to the orthographies of two versus one language benefit subsequent vocabulary learning? (b) Can an integrated model of the orthographic lexicon learn foreign vocabulary with more or less orthographic similarity to the native language?

At a bare minimum, foreign vocabulary knowledge entails learning to recognize or produce written or spoken word forms when prompted (González-Fernández & Schmitt, 2020). The brain's so-called *mental lexicon* is thought to store sub-lexical, lexical-semantic, and morphological (among other) information related to known vocabulary (Acha & Carreiras, 2014; Aitchison, 2012; Dijkstra, 2012). Researchers distinguish between two types of representations (or neural traces) in the mental lexicon: word forms, that is written (orthographic) or spoken (phonological) word representations; and meaning representations comprising knowledge or information arbitrarily mapped to one or many of these word forms (Aitchison, 2012). Learning foreign vocabulary essentially involves establishing new form and meaning representations in

the mental lexicon or validating existing form and meaning mappings (Marecka et al., 2021; Yang et al., 2015).

Individuals often jump-start their foreign vocabulary learning by relying on words that have forms (orthographic or phonological) similar to those in their native language (Bartolotti & Marian, 2017; Hayakawa et al., 2020). Intuitively, a word that looks or sounds more like a known native word should be easier to learn, irrespective of its meaning. For instance, an English speaker learning Spanish should find it easier to acquire the words “pera” (pear; a cognate) and “carta” (letter, not card; a false friend) than the word “perro” (dog; a non-cognate). Indeed, artificial vocabulary learning studies have shown that both cognates and false friends are acquired faster than non-cognate words (Marecka et al., 2021; Otwinowska et al., 2020). Even incomplete word overlap involving similar groupings of letters and sounds—reflecting sub-lexical orthotactic or phonotactic probabilities—can lead to faster vocabulary acquisition (Meyer & Schmitt, 2002; Storkel et al., 2006). This suggests considerable reliance on form representations. In other words, as long as a word is at least similar in its orthographic or phonological form to a word in a known language, learners can more rapidly integrate it into their mental lexicon.

While monolinguals learning a new language can only benefit from similarities to words in their first language, bilinguals can exploit similarities with both of their languages. Several studies have highlighted that bilinguals can transfer knowledge from any known language on a construction-by-construction basis (Jarvis & Pavlenko, 2007; Mihi, 2016; Rothman, 2015; Westergaard et al., 2017). Research also suggests that bilinguals incorporate novel words with orthographies similar to words in at least one of their languages faster than non-cognate words (Bartolotti & Marian, 2017). Furthermore, studies that have directly compared monolingual and

bilingual vocabulary learning have shown that bilinguals outperform their monolinguals peers when learning foreign-sounding unfamiliar words (Antoniou et al., 2015; Kaushanskaya & Marian, 2009b, 2009a). Together, these findings suggest that knowing two languages rather than one could provide a vocabulary learning advantage.

To our knowledge, no prior study has compared monolinguals and bilinguals learning novel vocabulary with varying orthographic similarity to their common native language. In Study 1 we thus tested monolingual (Spanish) and bilingual (Spanish-Basque and Spanish-English) participants' capacity to learn an artificial vocabulary comprising words that were either orthographically similar or dissimilar to their common native language (Spanish). Moreover, there is no mechanistic account for the combined effects of word form similarity and bilingual experience on foreign vocabulary learning. Therefore, in Study 2 we propose a simple computational model to explain the findings from Study 1. Earlier studies have hinted towards the existence of an integrated multilingual mental lexicon (Baxter et al., 2021; Dijkstra, 2012; Dijkstra & van Heuven, 2002; French & Jacquet, 2004). However, our study is the first to provide a computational implementation that corroborates behavioral evidence for these two vocabulary learning effects.

Study 1

In Study 1, we constructed a small (48-word) artificial written vocabulary—dubbed *Flavian* after the acronym for foreign language vocabulary (FLV)—as a benchmark for monolingual and bilingual participants' foreign vocabulary learning performance. Half of the vocabulary consisted of words with Spanish-like orthography (ES+ words), while the other half were orthographically dissimilar words (ES- words). Participants learned this vocabulary through

an active and explicit vocabulary learning task that involved recognizing and producing Flavian words *with feedback* across five learning blocks. There were two test phases separated by one night of sleep. The hypothesis was that the ES+ words with their Spanish-like orthography, would be acquired more accurately than the ES- words. Moreover, we expected bilinguals to outperform monolinguals in both types of word learning (i.e., show a general bilingual vocabulary learning advantage). Alternatively, these two variables might interact, with bilinguals only outperforming monolinguals on dissimilar but not similar words.

Critically, we included two bilingual groups to ensure that any effects we found were due to bilingual experience rather than specific language combinations. Spanish-English and Spanish-Basque bilinguals were compared to each other and to a Spanish monolingual group. All participants were from Spain, but the Spanish-Basque bilinguals were from a different region (Basque Country) than the Spanish and Spanish-English groups (Murcia).

Methods

Participants

Forty Spanish monolinguals ($M_{\text{age}} = 20.4$, $SD = 2.1$; 36 females), forty Spanish-English bilinguals ($M_{\text{age}} = 21.0$, $SD = 2.5$; 36 females), and forty Spanish-Basque bilinguals ($M_{\text{age}} = 21.5$, $SD = 2.6$; 29 females) participated in Study 1. Participants reported normal or corrected-to-normal vision and no history of major medical, neurological, or psychiatric disorders. The study protocol was approved by the Ethics Committee of the Basque Center for Cognition, Brain and Language (BCBL) and was carried out following the Code of Ethics of the World Medical Association (Declaration of Helsinki) for experiments involving humans. All subjects provided written informed consent prior to inclusion in the study and received monetary compensation for participating.

Before the experiment began, all participants completed a language background questionnaire, a picture-naming task, and a matrix reasoning task from the Kaufman Brief Intelligence Test (Kaufman & Kaufman, 2014) to measure non-verbal IQ. The linguistic questionnaire solicited information about age of acquisition, total exposure to each language, self-rated proficiency scales for each known language, and demographic factors such as age, gender, education level, and socioeconomic status (measured using average parental education level as a proxy). The picture naming task consisted of sixty-five images from the Basque, English, and Spanish Test (BEST) (de Bruin et al., 2017). Participants in the monolingual group named the images in Spanish and English, while the bilingual groups named them in both Spanish and their L2 (English or Basque). Additionally, participants in the bilingual groups completed the LexTALE test in both Spanish and their respective L2s (Izura et al., 2014; Lemhöfer & Broersma, 2012). The combination of these tests provided information on receptive and productive L2 vocabulary in the bilingual groups.

We compared the three groups using several ANOVAs with Helmert contrasts. In other words, the Spanish monolingual group was contrasted against the two bilingual groups at the first level, while the bilingual groups were contrasted with each other at the second level. A complete table with demographic information and statistical comparisons can be found in Appendix 1. The results suggested that the three groups did not differ in terms of age ($p = 0.204$, $BF_{10} = 0.303$), non-verbal IQ ($p = 0.619$, $BF_{10} = 0.303$), education level ($p = 0.320$, $BF_{10} = 0.204$), socio-economic status ($p = 0.836$, $BF_{10} = 0.092$), self-reported Spanish proficiency ($p = 0.419$, $BF_{10} = 0.166$), and Spanish picture naming ($p = 0.245$, $BF_{10} = 0.260$). As expected, the monolingual and bilingual groups differed in their exposure to Spanish, L2 age of acquisition, L2 exposure, L2 self-rated proficiency, and BEST picture naming in L2 (all $p < 0.001$). Critically,

the two bilingual groups did not differ in terms of L1 and L2 exposure, age of acquisition, self-rated proficiency, BEST picture naming, and LexTALE scores (all $p > 0.05$).

Materials

We created the Flavian artificial vocabulary by randomly producing nonwords with CVC-CV structure, where each C is a consonant and each V a vowel, and the hyphen marks the syllabic boundary. We used all possible consonants for the initial and second consonants, excluding the letters h, k, q, v, w, x, y, z. The letters l and r were excluded from the third consonant pool to avoid fluid consonant clusters and thus maintain the syllabic boundary (e.g., fl, fr, cr, cl). Initially, we generated 1,000 nonwords, from which we removed those that already existed in Spanish, English, or Basque. For each nonword, we calculated the gram and bigram frequency sum in Spanish and English using CLEARPOND (Marian et al., 2012) and in Basque using E-HITZ (Perea et al., 2006). We also obtained each nonword's orthographic Levenshtein distance (old20) to existing Spanish, English, and Basque words with the vwr package in R (Keuleers, 2013). Using these scores, we calculated a global composite orthographic similarity score by averaging the Z-scores for each variable; and then discarded nonwords with a composite score between -1 and 1. From the resulting list of 248 nonwords, we manually removed those nonwords that were very similar to each other and recalculated the orthographic similarity scores with respect to Spanish, reducing the list to a pool of 180 nonwords.

These 180 nonwords were rated by ten native Spanish-speakers on a scale from 1 (the nonword does not look at all like Spanish) to 4 (the nonword is very similar to Spanish). We included categories for whether the nonword resembled an existing Spanish word (due to its very similar phonology or orthography) or any other known language. Twenty real Spanish words were also included to control for each rater's attention during the task. We used the intra-class

correlation coefficient to measure the agreement between raters of the nonwords (Koo & Li, 2016). There was moderate agreement between the ten raters, using the two-way random effect model and the “average rater” unit ($\kappa = 0.74$, $F_{(199, 1791)} = 6.9$, $p < 0.001$). Thus, we included the Z-score of the average ratings per nonword into the composite score, using only the Spanish old20 and gram/bigram scores. Nonwords with scores between -0.5 and 0.5 were removed to create dichotomous categories based on their level of orthographic similarity (low/high) to Spanish. Finally, we manually selected 24 nonwords that were orthographically similar to Spanish from this list, hereafter ES+ words, and 24 nonwords that were orthographically dissimilar to Spanish, hereafter ES- words. The final Flavian word list can be found in Supplementary Table 1.

Procedure

Participants performed an active vocabulary learning task. At the beginning of the experiment, they were told they would learn vocabulary from a language named Flavian (Flaviano in Spanish). This instruction was included based on prior experiments and was intended to promote participant’s engagement with the task (Bartolotti & Marian, 2017). Each Flavian word was paired with a black and white depiction of a real object selected from the MultiPic dataset (Duñabeitia et al., 2018). The images were selected based on their low visual complexity, the gender of the depicted object, and had an H-index of 100—the percentage of agreement across different participants for the same image. The depicted objects were all concrete nouns (e.g., button, chair, pear). There were four counterbalanced lists to ensure that any effects were not due to specific pairings of Flavian words and images.

The vocabulary learning task involved recognizing and producing the Flavian words with feedback. We chose this procedure to maximize comparability with similar vocabulary learning

studies (Bartolotti & Marian, 2017; Hayakawa et al., 2020; Marecka et al., 2021). The participants first performed one block of familiarization with the Flavian words, where the pairings between the images and words were each shown once for 2 seconds. After the familiarization phase, they completed five blocks of alternating recognition and production tasks in the learning phase. The order of the trials in all these tasks was fully randomized.

In the 4-alternative forced-choice (4AFC) recognition task, participants saw a Flavian word at the center of the screen with four possible images (one target and three foils) presented in each corner of the screen. We ensured that each image appeared once as a target and three times as a foil. Participants used the keyboard (“d”, “c”, “k”, and “m” keys) to select the image that corresponded to the presented word without any time pressure. After submitting their responses, the correct image remained on screen alongside the word for 2 seconds, and a feedback message (“correct” or “incorrect”) appeared on the screen. The computer automatically recorded accuracy.

In the production task, participants saw an image at the center of the screen. They had to type the correct Flavian name of the depicted object on the keyboard and were allowed to make corrections before pressing enter to submit their final response. The computer automatically calculated word accuracy by assigning a score of 0.2 for each letter typed in its correct position for a maximum score of 1. Each additional letter past the maximum length for a Flavian word (5) received a 0.2 penalty, with a minimum score of 0. After submitting their responses, the correct Flavian name appeared below the typed word, alongside a feedback message (“correct”, “partially correct”, or “incorrect”) for 2 seconds. After 3 seconds, if participants had still not submitted a response, a message appeared on the screen encouraging them to type the word as best they could or to instead press enter to see the correct response and feedback messages.

After the learning phase, participants performed a computerized version of the Operation Span task (Unsworth et al., 2005) as a distractor task. This task lasted about 25 minutes and measured participants' working memory capacity. In this task, participants verified a series of simple mathematical equations (e.g., $[5 * 2] + 5 = 15$?) and decided whether they were correct or incorrect using the keyboard ("f" and "j" keys). After submitting the response for each equation, they saw a letter from the alphabet displayed for 2 seconds, which they were instructed to memorize. After a fixed number of equations, participants were instructed to type the letters presented during the equation verification task in the order in which they appeared. The task's difficulty increased gradually, starting with two equations and two letter trials as practice, then increasing up to seven equations and letters. Each difficulty level was repeated three times with different letters.

Finally, participants performed a test phase that consisted of two blocks of production and recognition trials: one administered after a short delay (D1) and another after a single night of sleep (D2). In these blocks, participants did not receive any feedback on typed or recognized words. However, to avoid participants rehearsing the Flavian words during the recognition task, they completed the production task first, followed by the recognition task. Otherwise, the trials in each block were precisely the same as in the learning phase.

Data analysis

Recognition and production accuracy during the learning phase were modeled separately using logistic and linear Growth Curve Analyses (GCA), respectively, in R (Mirman, 2017). GCA is a multi-level mixed model perfectly suited to capture the nested structure of time-course data while simultaneously quantifying group-level and individual-level patterns (Mirman, 2017; Mirman et al., 2008; Singer & Willett, 2009). We included second-order orthogonal polynomials

to reflect linear and quadratic changes across the blocks, using the group (i.e., SP-EN vs. SP-BQ vs. MONO), condition (ES+ vs. ES-) factors, and their interactions as fixed effects on all time-terms. Participant age, non-verbal IQ, gender, and Operation Span scores were also introduced as covariates in the models to account for any potential effects arising from individual scores on these variables. We subtracted the mean value from each continuous covariate before including it in the statistical models.

We contrast coded the condition and group factors in line with our hypotheses of a facilitatory effect for orthographically similar words and an overall bilingual advantage. The condition factor was deviation coded as -1 (ES-) and +1 (ES+). The group factor was reverse Helmert coded to first contrast the Spanish-English and Spanish-Basque groups (coded as -1 and 1) and then contrast the bilingual (BIL) and MONO groups (coded as -2 and 2, respectively). We included main effects and interactions for the time, condition, and group factors in the fixed effects but excluded any three-way interactions with the time-terms from the GCA models. Crucially, this approach differs from that used in prior studies, which instead focused on omnibus exploratory analytical methods (e.g., ANOVAs). We decided to adopt a confirmatory approach to more robustly evaluate the effects of bilingual experience using a priori planned contrasts. This approach makes the analyses directly interpretable without the need for corrected post-hoc tests (Schad et al., 2020).

We performed generalized and linear mixed-effects model (G/LMM) analyses for the test phase, using the recognition and production data, respectively. The condition and group contrasts were coded as in the learning phase models. However, in this case, the only additional factor was the test day (instead of the learning block), coded as -1 (Day 1) or +1 (Day 2). The G/LMM models were fitted using the *glmer* and *lmer* functions from the “lme4” package in R (Bates et

al., 2015). The degrees of freedom for the linear models were approximated using the Satterthwaite method as implemented by the lmerTest package in R (Kuznetsova et al., 2017). In contrast, the logistic GCA was estimated as an exact Z-test since the mean and standard deviation are known in the logistic model. Following standard practice, we tried to fit the maximal random-effects structure and reduced it to achieve convergence by eliminating the correlations between random slopes or the random slopes themselves (Barr et al., 2013). Each of the model's assumptions (e.g., variance inflation factor, collinearity, normality of residuals) were verified using the *performance* package for R (Lüdtke et al., 2021).

Finally, we report both the frequentist and Bayesian versions of the tests where possible. We opted to report the results from the Bayesian framework because these provide robust tests of the differences between groups while simultaneously testing the null hypothesis (Kruschke, 2010; van Doorn et al., 2020). Exact p-values are reported up to the 0.001 level for frequentist tests. For Bayesian tests, the exact Bayes Factor (BF_{10}) is reported from 0.001 to 100. BF_{10} values below 1 indicate more support for the null hypothesis, and values above 1 support the alternative hypothesis. We used uninformative priors for all Bayesian analyses. Paired-samples, one-sample, independent-samples, as well as ANOVA frequentist and Bayesian tests were all conducted in JASP, ensuring that the data met the corresponding assumptions (Love et al., 2019). To obtain an approximate BF_{10} from the G/LMM and GCA models, we contrasted nested models, including each fixed factor and interaction step-wise, against an intercept-only model with the same random-effects structure (Nakagawa et al., 2017; Wagenmakers, 2007). We calculated the BF_{10} using the Bayesian Information Criterion (BIC) of the intercept-only (m_0) and each fixed-effect model (m_1) with the following formula:

$$BF_{10} = \exp\left(\frac{BIC(m_0) - BIC(m_1)}{2}\right)$$

Results

As an initial step, we compared whether the counterbalance list influenced participants' performance during the learning and testing phases. For the learning phase, an ANOVA indicated no significant effect of the list on the last block of the recognition ($p = 0.499$, $BF_{10} = 0.113$) and production ($p = 0.404$, $BF_{10} = 0.136$) tasks. Similarly, there were no differences due to the list on the recognition test on Day 1 ($p = 0.336$, $BF_{10} = 0.162$) and Day 2 ($p = 0.366$, $BF_{10} = 0.131$), or on the production test on Day 1 ($p = 0.440$, $BF_{10} = 0.125$) and Day 2 ($p = 0.435$, $BF_{10} = 0.127$). Therefore, we did not include list as a factor in the final analyses.

We also calculated the score obtained by each participant in the Operation Span task as the sum of each fully correct letter recall, with a maximum score of 75 (Unsworth et al., 2005). We compared the three groups using an ANOVA with Helmert coding for the group factor. The results indicated no differences between the three groups ($F_{(2, 117)} = 2.527$, $p = 0.084$, $BF_{10} = 0.633$). Participants in the monolingual group had an average score of 55.1 (SD = 15.3), while those in the Spanish-English scored 56.7 (SD = 15.9), and the Spanish-Basque on average scored 61.9 (SD = 10.7). The Helmert contrasts also indicated no differences between the monolingual and bilingual groups ($p = 0.128$) and no differences between the two bilingual groups ($p = 0.103$). Thus, overall, the groups had comparable working memory capacity as measured by this task.

Table 1. *Logistic GCA of the recognition learning task.*

Fixed Effects	Estimate	SE	z	p	BF ₁₀
(Intercept)	1.203	0.079	15.317	< 0.001	-
Linear	1.767	0.075	23.464	< 0.001	> 100
Quadratic	-0.201	0.041	-4.891	< 0.001	> 100
Condition	0.094	0.015	6.286	< 0.001	> 100
SPBQ-SPEN	0.045	0.093	0.485	0.628	0.088
MONO-BIL	-0.117	0.054	-2.168	0.030	0.254
Linear x Condition	0.031	0.034	0.910	0.363	0.008
Quadratic x Condition	0.008	0.033	0.232	0.816	0.007
Linear x SPBQ-SPEN	-0.024	0.090	-0.268	0.789	0.078
Linear x MONO-BIL	-0.059	0.051	-1.169	0.243	0.124
Quadratic x SPBQ-SPEN	0.017	0.047	0.353	0.724	0.041
Quadratic x MONO-BIL	-0.020	0.026	-0.739	0.460	0.128
Condition x SPBQ-SPEN	0.008	0.018	0.437	0.662	0.003
Condition x MONO-BIL	-0.020	0.010	-2.012	0.044	0.029
<i>Covariates</i>					
Age	-0.021	0.021	-1.009	0.313	0.029
Non-verbal IQ	-0.005	0.004	-1.203	0.229	0.031
Gender	0.101	0.135	0.751	0.453	0.046
OSPAN score	0.004	0.003	1.245	0.213	0.080
<i>Random Effects</i>	<i>Group</i>	<i>Variance</i>	<i>SD</i>	<i>Correlation</i>	
<i>Participant</i>	(Intercept)	0.642	0.801		
	Linear	0.460	0.678	0.85	
	Quadratic	0.038	0.194	-0.67	-0.40

Note. Significant fixed effects terms are highlighted in bold. SE = standard error; SD = standard deviation; SPEN = Spanish-English bilinguals; SPBQ = Spanish-Basque bilinguals; MONO = monolinguals, BIL = bilinguals. Spanish-English bilinguals; SPBQ = Spanish-Basque bilinguals; MONO = Spanish monolinguals; BIL = bilinguals.

Learning phase

We performed the GCA analysis on the count of hits and misses using a binomial distribution and a logit link for the recognition task. The final model contained the by-participant random intercept and slopes for the linear and quadratic terms and a participant-by-condition random intercept. The results are shown in Table 1. The analysis revealed significant effects of the linear ($p < 0.001$, $BF_{10} > 100$) and quadratic ($p < 0.001$, $BF_{10} > 100$) terms, suggesting that individuals learned the words throughout the blocks in the recognition task. As expected, there was also a significant main effect of condition ($p < 0.001$, $BF_{10} > 100$), such that ES+ words

overall were recognized better than the ES- words. Moreover, the difference between Spanish-Basque and Spanish-English bilinguals was not significant ($p = 0.628$, $BF_{10} = 0.088$). Critically, bilinguals were better at recognizing the Flavian words than monolinguals throughout the learning phase ($p = 0.030$, $BF_{10} = 0.254$). Interestingly, there was a significant interaction between condition and the monolingual versus bilingual contrast ($p = 0.044$, $BF_{10} = 0.029$). It seems that the differences between monolinguals and bilinguals were larger for the ES+ condition than the ES- condition. The remaining two-way interactions between group, condition, time terms, or any covariates did not reach statistical significance (all $p > 0.05$, $BF_{10} < 0.2$). The learning trajectories for each group in the recognition task are depicted in Figure 1A. Notably, by the fifth block, participants in the Spanish monolingual group on average reached 82.5% (SD = 14.3) accuracy; those in the Spanish-English group averaged 86.9% (SD = 13.3), and the Spanish-Basque bilinguals averaged 87.8% (SD = 10.7).

Figure 1. *Recognition and production accuracy during the learning phase in Study 1.*

Note. Average observed accuracy (symbols, vertical lines indicate $\pm$ 95% confidence intervals) by group and condition for the recognition (A) and production (B) tasks. The solid lines depict the average GCA model predicted values. The conditions are plotted separately to avoid cluttering. The dashed line indicates chance-level accuracy. SPEN = Spanish-English bilinguals; SPBQ = Spanish-Basque bilinguals; MONO = Spanish monolinguals.

Table 2 shows the results for the linear GCA on production task accuracy. In this case, the analysis was performed on the summed partial accuracy data by participant, block, and condition. The final model converged with by-participant random intercept and random slopes for the linear and quadratic terms, a participant-by-condition intercept, and Linear and Quadratic random slopes. As in the recognition task, the results showed significant effects of the linear ($p < 0.001$, $BF_{10} > 100$) and quadratic ($p < 0.001$, $BF_{10} > 100$) time-terms. Accuracy was also significantly higher in the ES+ than the ES- condition ($p < 0.001$, $BF_{10} > 100$). There were no differences between the two bilingual groups ($p = 0.398$, $BF_{10} = 0.025$), but both bilingual groups outperformed the monolingual group ($p = 0.005$, $BF_{10} = 10.122$). Additionally, there were two significant two-way interactions. First, the linear time-term by condition interaction suggested that participants had a steeper learning slope in the ES+ than the ES- condition ($p < 0.001$, $BF_{10} > 100$). Second, the quadratic by condition interaction suggested that the curvature through the learning blocks was different for the ES+ and the ES- conditions ($p < 0.001$, $BF_{10} > 100$). The rest of the interactions were not significant (all $p > 0.05$, $BF_{10} < 0.5$).

Finally, among the covariates, there was a significant effect of participant gender ($p = 0.025$, $BF_{10} = 0.596$); it seemed that males performed better than females in this task. We refrain from discussing any gender differences in vocabulary learning, as these are outside the scope of this work. Participants' performance across the production learning blocks is depicted in Figure 1B. By the fifth block, participants in the Spanish monolingual group reached an average score of 51.7% (SD = 17.0), participants in the Spanish-English group a score of 63.4% (SD = 17.2), and those in the Spanish-Basque bilingual group 61.0% (SD = 19.6).

375 **Table 2.** *Linear GCA of the production learning task.*

Fixed Effects	Estimate	SE	df	t	p	BF ₁₀
(Intercept)	9.627	0.342	124.1	28.183	< 0.001	-
Linear	7.759	0.241	117.3	32.207	< 0.001	> 100
Quadratic	-1.357	0.128	117.3	-10.571	< 0.001	> 100
Condition	1.329	0.091	116.4	14.619	< 0.001	> 100
SPBQ-SPEN	-0.343	0.405	117.0	-0.848	0.398	0.025
MONO-BIL	-0.679	0.235	118.7	-2.884	0.005	10.122
Linear x Condition	0.550	0.112	118.9	4.913	< 0.001	> 100
Quadratic x Condition	-0.295	0.086	119.0	-3.439	0.001	> 100
Linear x SPBQ-SPEN	-0.166	0.295	117.5	-0.564	0.574	0.033
Linear x MONO-BIL	-0.246	0.170	117.1	-1.443	0.152	0.066
Quadratic x SPBQ-SPEN	-0.031	0.157	117.5	-0.200	0.842	0.011
Quadratic x MONO-BIL	-0.019	0.091	117.1	-0.209	0.835	0.159
Condition x SPBQ-SPEN	0.164	0.099	116.3	1.650	0.102	0.001
Condition x MONO-BIL	-0.071	0.057	115.8	-1.232	0.220	0.486
<i>Covariates</i>						
Age	-0.134	0.103	113.4	-1.301	0.196	0.008
Non-verbal IQ	-0.017	0.020	112.8	-0.847	0.399	0.001
Gender	1.505	0.662	112.6	2.275	0.025	0.596
OSPAN score	0.021	0.017	112.6	1.243	0.216	0.007
<i>Random Effects</i>	<i>Group</i>	<i>Variance</i>	<i>SD</i>	<i>Correlation</i>		
<i>Participant by Condition</i>	(Intercept)	1.697	1.303			
	Linear	1.573	1.254	0.49		
	Quadratic	0.339	0.582	-0.90	-0.56	
<i>Participant</i>	(Intercept)	11.690	3.419			
	Linear	5.450	2.335	0.54		
	Quadratic	1.089	1.044	-0.86	-0.66	

376 *Note.* Significant fixed effect terms are highlighted in bold. SE = standard error; SD = standard deviation; SPEN =
377 Spanish-English bilinguals; SPBQ = Spanish-Basque bilinguals; MONO = Spanish monolinguals; BIL = bilinguals.
378

Figure 2. Recognition and production accuracy during the test phase in Study 1.

Note. Raincloud plots showing the probability density of the accuracy scores by condition, group, and day-of-test. The center of the boxplot indicates the median, and the limits of the box define the interquartile range (IQR = middle 50% of the data) for each group. Dots reflect individual participant scores. SP-EN = Spanish-English bilinguals; SP-BQ = Spanish-Basque bilinguals; MONO = Spanish monolinguals; D1 = day 1; D2 = day 2.

Test phase

A GLMM on the recognition test scores revealed a significant effect only for the condition ($p = 0.033$, $BF_{10} = 0.439$). All other main effects and interactions were not significant (all $p > 0.05$, $BF_{10} < 0.3$). For brevity, we report the full table of results in Appendix 2. For all groups, recognition test performance did not decrease from one day to the next, but the differences between monolinguals and bilinguals observed during the learning phase disappeared. The scores by condition, group, and day are presented in Figure 2A. On average, participants in the monolingual group scored 85.1% (SD = 11.8) on day 1, and 84.8% (SD = 12.7) on day 2. Similarly, participants in the Spanish-English bilingual group scored 88.5% (SD = 11.8) and 88.5% (SD = 11.9) on days 1 and 2, respectively. Finally, the Spanish-Basque group averaged 88.8% (SD = 10.6) on day 1 and 87.1% (SD = 11.5) on day 2.

An LMM of the production test scores (shown in Appendix 3) indicated that participants' performance on the production task decreased on day 2 ($p < 0.001$, $BF_{10} > 100$). As in the recognition task, participants performed better with ES+ than ES- words on both days ($p < 0.001$, $BF_{10} > 100$). The results revealed no differences between the Spanish-Basque and Spanish-English bilinguals ($p = 0.357$, $BF_{10} = 0.075$), but both bilingual groups outperformed their monolingual peers ($p = 0.002$, $BF_{10} = 3.033$). There were no significant two-way interactions between the day, condition, or group contrasts (all $p > 0.05$, $BF_{10} < 0.2$). The production scores by condition and day are depicted in Figure 2B. Participants in the Spanish monolingual group averaged 51.7% (SD = 17.7) and 47.6% (SD = 16.7) on days 1 and 2, respectively. Individuals in the Spanish-English bilingual group scored 64.1% (SD = 16.4) on day 1 and 61.6% (SD = 18.1) on day 2. Finally, the Spanish-Basque bilingual group averaged 61.0% (SD = 20.3) on day 1 and 57.0% (SD = 21.6) on day 2, respectively. Note that these scores are based on participants'

partial accuracy, which means that, on average, participants could partly produce around half of the words (i.e., 24 words) in the experiment ¹.

Summary

In Study 1, we tested the roles of orthographic similarity and bilingual experience in vocabulary learning. This experiment measured both the learning trajectory and outcomes after learning an artificial vocabulary (Flavian) with varying degrees of orthographic similarity to Spanish. We tested participants' receptive and productive vocabulary using two tasks. Overall, the results showed consistent effects of orthographic similarity during both the learning and testing phases. Words that were more similar to Spanish (ES+ condition) were learned faster and remembered better during the test than less similar (ES- condition) words by all groups in both the recognition and production tasks. These findings are consistent with a growing literature suggesting a role of orthographic and phonological similarity during foreign vocabulary learning (e.g., Bartolotti & Marian, 2017; Hayakawa et al., 2020; Marecka et al., 2021).

Moreover, the results revealed a difference between monolinguals and bilinguals, but no differences between the two bilingual groups. Both bilingual groups outperformed their monolingual peers during the learning phase in terms of recognition and production accuracy. Bilinguals were also better at producing but not recognizing the words during the test phase. These two findings align with previous literature showing a bilingual vocabulary learning advantage (e.g., Antoniou et al., 2015; Kaushanskaya & Marian, 2009b, 2009a). However, the findings of this experiment extend the existing literature in two important ways.

¹ Indeed, considering responses with a score of 0.8 and above as correct and performing a GLMM analysis using absolute accuracy instead of partial accuracy led to similar results, with lower scores across the board and a global average of around 40% in the ES- condition and 50% in the ES+ condition.

First, the results of this experiment show how differences emerge across the time-course of learning, with bilinguals outperforming monolinguals across the learning blocks in both recognition and production tasks. Curiously, bilinguals outperformed monolinguals in the ES+ (but not the ES-) condition after just the familiarization phase, particularly in the production task. It is possible that, compared to monolinguals, bilinguals were more willing to produce words after having just seen them once. Nevertheless, the group differences disappeared during the recognition but not the production tests. In other words, measuring only the outcome of learning would have led to observing a lack of differences at the receptive vocabulary level. Admittedly, the recognition task was less challenging than the production task. The number of items (48) and extensive practice with the recognition task might have nudged participants' accuracy towards a ceiling, thus eliminating any differences between the groups.

Second, differences between the groups were evident in both the ES- and ES+ conditions supporting the idea that bilingual's enjoy a vocabulary learning advantage for both similar and unfamiliar novel words. As suggested by prior studies, this bilingual advantage could be related to mechanisms such as enhanced orthographic or lexical-semantic networks, as well as enhanced working memory capacity (Hirosh & Degani, 2018; Kaushanskaya & Marian, 2009b). However, there were no differences between the groups on their working memory capacity as measured by the Operation Span task, nor did this variable significantly account for the results. Therefore, it is still unclear how experience with two languages can foster novel vocabulary acquisition, irrespective of the specific language pairs. To address this gap, in Study 2, we proposed and developed a computational model that learned written words in a second and third language.

Study 2

Due to the orthographic nature of Study 1, the findings provide a testable hypothesis regarding the role of bilingual input in the organization of word forms in the mental lexicon. Because bilinguals gain experience with potentially distinct orthographic patterns (orthotactics) in two languages, the bilingual orthographic lexicon might more flexibly integrate both similar and dissimilar novel word forms than a lexicon that operates on only one language. Nevertheless, words which are orthographically more similar to other lexical entries should still be acquired more accurately than those which are dissimilar. However, despite numerous efforts to formalize the bilingual mental lexicon using computational approaches (e.g., Dijkstra et al., 2019; French & Jacquet, 2004; Li & Grant, 2019), the basis for these seemingly disparate learning effects remains largely unexplored.

Theoretical and computational models of the mental lexicon posit that word form representations are distinct from meaning representations (Dijkstra, 2012). Some models use *localist* representations of whole word forms and meanings, whereas others use *distributed* representations, treating word forms or meanings as compositions of many features (Holman & Spivey, 2016). The second language processing literature concurs that representations of meaning are common to native and second languages, but there are two contrasting views regarding word form representations (de Groot, 1992; French & Jacquet, 2004). Proponents of the *language-selective* view argue that form representations are unique for each language or that additional mechanisms (e.g., bottom-up or top-down language tags) modulate which set of representations is more active for a specific word (Jacquet & French, 2002; Kroll et al., 2010). Conversely, under the *language-nonselective* view, word form representations are unified in the two languages (De Groot et al., 2000).

On the one hand, localist models, such as the Bilingual Interactive Activation Model (Dijkstra & van Heuven, 1998, 2002; Grainger et al., 2008) and the Revised Hierarchical Model (RHM) (Kroll et al., 2010), are highly regarded for their ability to account for multiple phenomena in bilingual word recognition and language representation, such as inter-language competition, and language switching effects. These models focus primarily on word processing rather than word learning and thus provide only verbal accounts of foreign vocabulary acquisition. For example, the RHM proposes that, during second language learning, individuals initially establish a link between form representations in the second language (L2) and their corresponding form in the native language (L1), without a direct link to meaning representations. With increased exposure to the L2, the connection between L2 words and meaning strengthens, while the original link between L1 and L2 word forms weakens. It is unclear how these models could account for the facilitatory effects of form similarity and bilingualism during foreign language learning, as the representations of word forms in these models are localist in nature and unique for each language.

On the other hand, three distributed models have made important advances regarding bilingual mental lexicon development. The Bilingual Simple Recurrent Network—trained with simple sentences in English and French (e.g., *man lift boy*; *garçon voit ballon*)—was one of the first models to reveal that lexical representations clustered by language without the need for explicit language tags (French, 1998). Following these results, the Dev-Lex-II model simulated the developmental differences caused by early vs. late second language learning, showing similar language separation for phonological word forms (Li & Farkas, 2002; Zhao & Li, 2010). Finally, the Conceptual Feature Mapping model (Lee et al., 1999) provided a verbal explanation for the facilitatory effects of word form similarity on foreign vocabulary learning. According to this

model, learning a foreign word requires a modification of the connections from the word form layer to an intermediate and localist “lemma” layer or from this intermediate layer to the relevant meaning representations, depending on whether the target word’s form or meaning overlaps with its native language counterpart. Still, it is hard to extend this idea to more than two languages, as these lemma nodes are localist, and it would be necessary to add a new node for every “new” language.

Localist models are highly interpretable and can be effectively compared to human behavior, but they require extensive manual engineering of the architecture and parameters, which does not allow to investigate the underlying learning mechanisms. Conversely, distributed models use simple learning mechanisms to create effective representations , but have not yet been compared directly to human behavior (Holman & Spivey, 2016). Moreover, to date these models have only tackled small-scale simulations using carefully selected subsets of words (Li & Grant, 2019), limiting their generalizability. Finally, none have been extended beyond second language learning to explain potential differences between monolingual and bilingual vocabulary learning. For these reasons, in Study 2, we developed a computational model of the orthographic lexicon. It is instantiated as a recurrent neural network that can learn written vocabulary by implementing a unified, distributed, and dynamic view of the orthographic lexicon.

The CLOUD model

CLOUD, *Constrained Learner of Orthography: Unified, Distributed, and Dynamic*, is a character-level recurrent model we developed with three important constraints. First, following the language-nonselective view predominant in the literature (see Baxter et al., 2021), the model stores the word form representations of either one or two languages in a *unified* structure. This constraint potentially forces the model to develop representations that can distinguish between

the languages. Second, to test for the effects of orthographic similarity during foreign language learning, the model contains *distributed* representations of letters and word forms implemented as numeric vectors (or patterns of activation). Previous studies have used distributed word-level representations to investigate the organization of words in the bilingual lexicon and report separation between the languages despite the lack of language-specific nodes (French, 1998). However, these lexicons have not been implemented at the character level. Third, the model adjusts these distributed representations *dynamically* during vocabulary learning. This constraint implies that learning any new word will change the representations of existing words in the lexicon. This dynamic constraint is backed by recent research suggesting that mere exposure to words in a different language changes orthographic processing and word learning in the native language, hinting at a dynamic lexicon (Bice & Kroll, 2015, 2019).

We structured the CLOUD model as a three-layer recurrent neural network that learned its distributed representations by predicting the probabilities for multiple words based on each potential subsequent character—a mechanism loosely analogous to the predictive coding framework of the nervous system (Huang & Rao, 2011; Rao & Ballard, 1999). Recurrent neural network models can approximate the probabilities of natural languages (French & Jacquet, 2004; Mikolov et al., 2010). They have been used extensively in the natural language processing literature, where they are known as language models (e.g., Mikolov et al., 2010; Sundermeyer et al., 2013; Williams et al., 2015). Since recurrent models keep track of current and past information, they can form representations of the co-occurrence patterns in the input (Testolin et al., 2016). Taking sentences as an example, a word-level model contains representations of word co-occurrence. For instance, a word-level model could output a higher probability of “house”

following “my” than “lie” following “my”. Similarly, a character-level model contains information about certain letters following others within words in a language.

Figure 1 exemplifies the inner working of the CLOUD model using the word “model” as an example. In essence, at each time step, the model processes a letter as input and tries to predict the next character (Figure 3A). The first layer, called the Embedding layer, transforms each letter into a distributed 16-dimensional activation vector. While admittedly an over-reductionist approach, we chose to add this layer to exemplify how the printed letter becomes an internal representation (Finkbeiner & Coltheart, 2009; Rapp & Caramazza, 1997). After this, 128 Long Short-Term Memory (LSTM) hidden nodes store the distributed orthographic word form representations (Hochreiter & Schmidhuber, 1997). These recurrent nodes allow the model to develop sensitivity to long- and short-term orthographic dependencies within words. The criteria for selecting the number of dimensions in each layer are detailed in the Methods section and in Supplementary Figure 1. Lastly, the Output layer encodes the successor character’s probability distribution given a sequence of preceding characters (Figure 3B). The model was trained using error backpropagation based on the discrepancy between the predicted character and the correct character in a word (Rumelhart et al., 1995; Werbos, 1990). Using this self-supervised procedure for predicting the next character in a word, the CLOUD model can learn the orthotactic patterns underlying words in multiple languages.

A second reason for naming the model CLOUD is its capacity to generate *word clouds* using the representations learned by the LSTM nodes (Figure 3C). To obtain the representation of a word in the CLOUD, the LSTM outputs at each time step are averaged. Then, we project each word’s 128-dimensional vector onto a 2-dimensional space for visualization using t-distributed stochastic neighbor embedding (t-SNE) method (Van Der Maaten & Hinton, 2008).

These word clouds help us visualize how words cluster according to their orthotactic patterns in different languages. They also allow us to compare the representation of any word (or nonword) to other words in the dataset so as to identify similar words, further boosting the interpretability of the CLOUD architecture. For instance, as expected, the word “model” is closer to orthographically similar words in the dataset, including its Spanish translation equivalent, “modelo” (Figure 3D). Since the model learns from individual letters and not whole words, its distributed representations (and outputs) are not limited to specific words or languages. This makes the CLOUD architecture ideal for probing questions about monolingual and bilingual written vocabulary learning. An interactive version of Figure 3C can be viewed at <https://tabsoft.co/3tvDuST>.

In developing this model, we aimed to answer three specific questions. (1) Can a unified model learn the orthotactic patterns of two languages without language-specific nodes? (2) Do the internal representations of the model contain information about the language of a word? And critically, (3) could this model emulate the effects of orthographic similarity and bilingual experience observed in Study 1? We trained a monolingual and two bilingual *versions* of the CLOUD model to simulate the findings from Study 1. To serve this purpose, the versions had to meet four criteria. First, they needed to have a sufficiently simple architecture that the relation between input and output would be at least partially interpretable. Second, the versions should not differ in terms of their architecture but only in terms of their input. Third, there should be an appropriate metric for assessing the performance of these models. Fourth, in comparing monolingual and bilingual versions, their performance on this metric should be matched. Below, we explain how we addressed these desiderata.

Figure 3. *The CLOUD model.*

Note. (A) Depiction of the CLOUD model architecture. The model processes each character sequentially, using the current character and an internal (context) state as inputs, and predicting the next character in the sequence in a recurrent and self-supervised manner. The model selects the next character from a pool of 27 characters, including 26 letters of the alphabet plus a space token (here marked as #). After training, the model approximates the next character's probability distribution given the previous sequence of characters. All connections are learnable parameters in the CLOUD architecture. (B) An example plot of the top five successor character's probabilities at every time-step in processing the word "model" as input. At time-step 4 (t_4), after processing the sequence "#MOD", the model predicts a 49% probability that the next character in the sequence is "E". (C) A word cloud created using the LSTM hidden representations of the entire Spanish-English word dataset. The marginal distributions suggest a slight separation between the two languages. Hand-picked examples on the right suggest that some English words cluster based on specific patterns that do not exist in Spanish, such as beginning with "w", ending with "y", or containing "k". The examples on the left are a cluster of Spanish and English words that begin with "p", including perfect cognates (e.g., plural) and orthographic neighbors (e.g., plum, pluma). (D) The top 15 most similar English and Spanish words to the word "model". Pairwise similarity scores were calculated using cosine similarity, the dot product of the L2-normalized vector representations. The dimensions are jittered to minimize word overlap. The top words include those with similar orthography, beginning with "mo" (e.g., motel, modal, molde).

Methods

Model architecture

The CLOUD architecture contains three fully connected layers. At each time step, the model receives one character as a categorical index from 0 to 26 for a total of 27 characters. The characters include the 26 letters of the alphabet, plus a space character that indicates the beginning or end of a word (here depicted as #). After receiving the input, the Embedding layer converts each character index to a 16-dimensional distributed vector using a lookup table with parameters that were learned during training. This process would be analogous to learning an abstract letter identity, which could very well be learned from pixel-level visual input as in prior studies, though this process would carry an excessive computational burden (Testolin et al., 2017). We chose this layer's dimensions as the power of 2 closest but smaller than the alphabet size to obtain a distributed representation of each character. Although these distributed character representations can be individually interpreted, the organization of individual characters in monolingual and bilingual input is beyond the scope of this study.

The second layer contains 128 recurrent LSTM nodes. We selected the final number of nodes for the LSTM layer after exploring the model's performance with varying nodes (see Supplementary Figure 1). The LSTM nodes capture long- and short-term dependencies in the input using two 128-dimensional distributed representations. These representations are respectively called cell states and hidden states. The cell and hidden states are combined with the Embedding layer's output through a series of gating mechanisms at each time step. First, the *forget gate* combines the information from the current input and the previous hidden state to decide which information to remove from the cell state. In parallel, the *input gate* decides which information to add to the cell state using the combined input and hidden state. The LSTM layer

uses these two gates to produce the next cell state. Then, it combines this new cell state with the *output gate* to calculate what should be propagated to the next hidden state. This process can be summarized using the forward pass equations shown in Supplementary Equations 1.

The Output layer implements a multinomial logistic regression. This layer uses the hidden state produced by the LSTM layer to output the logits for each possible character, implemented with the equation

$$\text{logits}_t = W_{ol} \cdot h_t + b_{ol} \quad ; \quad W_{ol} \in \mathbb{R}^{27 \times 128}; b_{ol} \in \mathbb{R}^{27} \quad (1)$$

where logits_t is a 27-dimensional vector of logits for each possible character output, W_{ol} and b_{ol} are the output layer's weight and bias parameters, and h_t is the 128-dimensional hidden output from the LSTM layer. The weight parameters are initialized following standard practice (Glorot & Bengio, 2010), sampling randomly from a uniform distribution ranging from $-1/27^{0.5}$ to $1/27^{0.5}$, where 27 is the number of output dimensions (here the 27 characters also used as input).

The model learns by predicting each word's next character and receiving a prediction error signal that updates the Embedding, LSTM, and Output layer weight and bias terms. This mechanism is called backpropagation (Rumelhart et al., 1995; Werbos, 1990). We computed the prediction error using the cross-entropy loss function

$$\text{loss}(\text{logits}, \text{character}_{\text{index}}) = -\text{logits}_{\text{character}_{\text{index}}} + \log \left(\sum_{i=0}^{27} \exp(\text{logits}_i) \right) \quad (2)$$

that takes the negative of the expected character's logit and adds the logarithm of the sum of all logits' exponents in the output vector.

During learning, the backpropagation algorithm adjusted every learnable parameter in the model. This algorithm requires calculating the partial derivative of Eq. 2 with respect to each parameter to determine in which direction to update them. We implemented the CLOUD

architecture using PyTorch (Paszke et al., 2017), a Python-based framework that provides automatic differentiation capabilities and already contains the optimized Embedding, LSTM, and Output layers described above. The final model had 78,812 learnable parameters²; the objective was to minimize the prediction error (loss function) by adjusting these parameters.

Materials

Pre-training datasets. We started with 44,853 Spanish words from the SPALEX dataset (Aguasvivas et al., 2018), 61,851 English words from the English Crowdsourcing Project (L2 version) (Mandera et al., 2020), and 74,490 Basque words from the EHME dataset (Acha et al., 2014). We first reduced the number of words in each dataset by discarding words with a frequency lower than the median value and limiting the length between 3 and 10 characters. These filters reduced the Spanish words to 19,592, the English words to 28,174, and the Basque words to 37,978. Every letter with a tilde (e.g., é, ñ) was replaced with its corresponding Roman alphabet counterpart (e.g., e, n) and duplicate words in each dataset were removed. Recent evidence suggests that processing does not differ between the tilde and non-tilde versions of these letters in Spanish speakers (Perea et al., 2020). Moreover, this step reduced the final number of characters to the 26 letters common to all languages under study.

The next step involved matching the word length distributions in the datasets. We sampled the minimum number of words from each dataset at every possible word length to accomplish this. The final datasets contained 19,516 words each. We randomly selected 1,640 words for testing from each dataset, leaving 17,876 words for training. The test words were used to calculate the models' performance on unseen words. We constructed a Spanish-English

² There was an additional padding character in the vocabulary used internally for processing multiple words in batches. Therefore, in total there were 464 parameters in the Embedding layer, 74,752 parameters in the LSTM layer, and 3,612 parameters in the Output layer.

dataset by combining the Spanish and English training and test words and a Spanish-Basque dataset by combining the Spanish and Basque words. Importantly, even though we randomly sampled the words to assign them to the train and test sets there was no significant difference in word length between the two lists (all $p > 0.05$).

The monolingual CLOUD version performed the character prediction task described above over the 17,876 Spanish words. The Spanish-English bilingual version (depicted in Figure 3C) learned from a subset of 60% of the Spanish words (10,725) and 40% (7,150) of words selected at random from the Spanish-English dataset. Finally, the Spanish-Basque bilingual version used the same proportion (60/40) from the Spanish and Basque datasets. We selected these percentages to reflect the reality of bilingual exposure within Spain and roughly approximate participants' overall exposure in Study 1. Notably, the amount of vocabulary used in the present modeling work represents an almost ten-fold increase in input over previously reported models, which contained around 1,700 words at most (Li & Grant, 2019). Our choice of vocabulary is better aligned with real-world scenarios, considering that the average young adult controls more than 25,000 words (Aguasvivas et al., 2020; Brysbaert et al., 2016).

Adapted Spanish Lexical Decision Task. It is essential to have a measure that adequately accounts for model performance. Traditionally, the measure of choice has been top-k accuracy in predicting the successor character (i.e., is the correct letter included in the model's top-k predictions?). However, language models typically do not score high on this measure, as a precise prediction of the successor character is unlikely. Suppose a character-level model only learned the words "care" and "cars" in equal proportions. In that case, the probability of predicting the letter "e" after seeing "car" would be approximately equal to that of predicting "s". Thus, the maximum theoretical top 1 accuracy for this simplified model would be 50%, while

top 2 accuracy would be close to 100% since there are only two possible choices. Extending this observation to a scaled-up scenario explains why character-level models rarely perform above 35-40% using top k accuracy metrics where k has a low value. Indeed, performance above the 50% level could indicate severe overfitting to the training data, leading to poor performance on unobserved words.

A prior study has suggested that using a 2AFC adaptation of the Lexical Decision Task (LDT) provides an alternative measure to compare character-level model performance that avoids the problem with top-k accuracy (Le Godais et al., 2017). In this adapted LDT, the character-level model calculates the probability of two words matched in length (one target and one foil) by multiplying its output probabilities at each time step (see Figure 3B for a visual depiction with one word). Ideally, the probability for existing words should be higher than that of non-words for a trained model. This adapted LDT also addresses the issue of multiplicative probabilities—whereby multiplying probabilities will yield smaller values for longer words—by matching the target and foil words in their length. This adaptation has been previously used in the psycholinguistic literature with human participants (Baddeley et al., 1993). For these reasons, we constructed an adapted Spanish LDT dataset for measuring and matching the CLOUD models' performance.

We selected a set of non-words from the SPALEX dataset (Aguasvivas et al., 2018). These non-words had previously been rated by human participants, yielding information about how well they could categorize them as non-words. This information was essential to selecting and matching the words and non-words. Initially, there were 56,861 non-words in the dataset. We selected those non-words rated correctly by more than 30 participants at an average percentage in the 72% to 95% range. In other words, these non-words were neither extremely

easy nor extremely challenging to discriminate. We further restricted the non-words length between 3 and 10 characters, replaced any tilde character, removed duplicates, and matched the length distributions to the Spanish words. The final list contained 19,516 non-words, paired by length to the existing Spanish dataset and separated into training and testing datasets. We did not enforce any control beyond these measures (e.g., using similar orthographic structures). An initial analysis with 20 untrained CLOUD models indicated that average performance did not differ significantly from chance ($M_{acc} = 49.7\%$, $SD = 1.0$, $t_{(19)} = 1.342$, $p = 0.196$), confirming that the dataset was not inherently biased towards words or non-words.

Flavian vocabulary. The Flavian vocabulary was the same as in Study 1. For more information about the construction of this vocabulary, see the Methods section in Study 1. Supplementary Table 1 contains the vocabulary and additional metrics.

Procedure

Model pre-training. Since the CLOUD architecture was the same for the monolingual and bilingual versions, it was essential to pre-train the versions to approximate the orthographic lexicon of an adult individual. We call this step *pre-training*. It entailed exposing different versions of the CLOUD model to words from Spanish, English, or Basque. In other words, the architecture of the model was fixed, but model versions differed due to their exposure to the orthography of words in one or two languages. Training on words from these distinct word sets resulted in three distinct versions of the CLOUD model: Spanish monolingual (MONO), Spanish-English bilingual (SP-EN), and Spanish-Basque bilingual (SP-BQ). The MONO version learned from 17,876 (100%) Spanish words. In contrast, the bilingual (SP-EN and SP-BQ) versions were trained on 60% (10,726) Spanish and 40% (7,150) L2 words, randomly selected from their respective pre-training datasets. There were ten runs with different random

initializations for each version. This increased the variability of the model output and allowed us to statistically compare them. The words were presented at random to these models, meaning that a bilingual model could see a word in Spanish followed by a word in the L2.

During each pre-training epoch, the models performed the character prediction task mentioned above over their entire respective datasets. This process was repeated for all words in the monolingual or bilingual training sets, shuffled at the start of each epoch. We employed three techniques to improve computational performance during pre-training. The first technique was to allow the model to process batches of 82 words instead of processing words one by one. The second technique was to apply a baseline learning rate of 0.002, adapted during pre-training using the Adam optimizer (Kingma & Ba, 2015). We did not explore how different learning rates affected the results presented in this study and instead chose a value commonly used in the deep learning literature (Le Godais et al., 2017; McMahan & Rao, 2019). Finally, we pre-trained the model using GPU capabilities, which allowed us to run all vector and matrix operations in parallel.

Adapted Spanish LDT. The models were trained to criterion using the adapted Spanish LDT. Empirical evidence from a Spanish lexical decision megastudy suggests that monolingual and bilingual participants do not differ in terms of LDT accuracy (Aguasvivas et al., 2020). Therefore, the different versions and runs of the CLOUD models needed to show comparable performance on this adapted Spanish LDT. Each CLOUD version and run performed an identical adapted Spanish LDT, calculating the probabilities for each pair of length-matched items: one target and one foil. The item with higher probability was selected as the model's response and an accuracy measure based on this response was calculated. This process was repeated for all words in the LDT dataset. We used the adapted Spanish LDT training set to match each run and version

of the CLOUD model by setting an adaptive accuracy threshold that started at 65% since the runs quickly reached this threshold after 1 or 2 training epochs. Upon reaching this threshold, the state of that run’s parameters was automatically saved, and the threshold increased by 5%. We used states corresponding to the maximum threshold achieved by all runs in all subsequent analyses and simulations. Pre-training LDT accuracy and loss over 100 epochs for each of the CLOUD versions is presented in Supplementary Figure 2.

Adapted Flavian vocabulary learning task. After pre-training and matching the LDT performance of each run, the monolingual and bilingual CLOUD versions performed an adapted version of the Flavian vocabulary learning task in Study 1. However, since the CLOUD model only learned to produce the successor character distribution when prompted by a context, the versions performed adapted *recognition* and *production* tasks. For the *recognition* task, we randomly assigned a numeric label from 0 to 47 to each Flavian word. We added a recognition module on top of the CLOUD architecture that predicted the numeric label of the Flavian word. This “read-out” module performed a multinomial logistic regression taking each Flavian word’s 128-dimensional hidden representation averaged over all time steps as input and predicting the probability of the correct label, written as

$$label = W_l \cdot h_w + b_l ; W_l \in \mathbb{R}^{48 \times 128}; b_l \in \mathbb{R}^{48} \quad (3)$$

where *label* is a 48-dimensional vector containing each label’s logits from a Flavian word’s hidden representation, and h_w , W_l and b_l are learnable weight and bias parameters initialized as in Eq. 1. This module loosely resembles the task subsystem employed by bilingual models such as the BIA+ (Dijkstra & van Heuven, 2002). In other words, it takes the orthographic representations of a word and executes an action, which in this case entails selecting its appropriate label.

Since the participants in Study 1 performed a 4AFC task, we adjusted the recognition scores by selecting the logits from the target label and three randomized labels and then calculating the softmax function (i.e., the exponent of the logits divided by the sum of the exponents). We then extracted the probability of the model selecting the correct label for the seen Flavian word from this adjusted vector. This process is equivalent to performing a transformation based on the Luce choice axiom (Jessie & Saari, 2016). The production task needed minimal adaptation, as the model could already produce the succeeding character from a prior context. Instead of computing the produced word's accuracy as in Study 1, we calculated the model's probability of producing this word by multiplying the probability obtained for each of the word's characters during learning. We further boosted the probability by multiplying it by the length of each Flavian word (5), thus shifting all probabilities upwards. All analyses and visualizations were performed on the logarithm of the probabilities.

The models learned the Flavian words by backpropagating the loss during the recognition and production tasks using the same hyperparameters as in the pre-training task. Each model performed a familiarization task, followed by five alternating recognition and production learning blocks, similar to participants in Study 1. However, since there is no information decay in the CLOUD model (i.e., the model does not forget over time), we did not attempt to replicate the test phase from Study 1.

Data analysis

The analysis plan was divided into three stages. The first step involved matching the different CLOUD model versions and runs based on their LDT accuracy. It was essential to verify that the different versions of the models performed comparably on this task. However, while the adaptive threshold was used to select and match the performance of each run on the

training LDT dataset, we also computed their performance on the unseen test LDT words. The accuracy scores were then analyzed using ANOVAs for each model version (SP-EN, SP-BQ, MONO) and set (train or test) separately. The version factor was coded using a Helmert contrast to first compare the monolingual with the two bilingual versions and then compare the two bilingual versions. Finally, we compared the achieved accuracy of all models to an empirical chance level obtained by averaging the scores of 20 untrained CLOUD models on the same LDT datasets.

The second step was to evaluate the language organization within the different versions of the CLOUD models. We incrementally obtained representations for each character in each word in the Spanish-English and Spanish-Basque validation and test sets. Then, a series of logistic regression classifiers were employed to categorize the representations at each time step into one of two classes: Spanish (L1) or English/Basque (L2). The logistic regression classifiers used L2 (ridge) regularization, with a regularization strength of 1. They were trained using the “lbfgs” solver as implemented by the scikit-learn Python module (Pedregosa et al., 2011), with 10^9 maximum iterations and a fixed seed for replicability (404). The classifiers were only trained on test set words (not seen during training by the models) to minimize computation time. Half of the test set representations (820 words) were used to train the models. The other half (820 words) was used to calculate the probability of the logistic regression model selecting the correct language. This procedure was repeated at every possible character position, from 0 (the space symbol) to 10 (the character before the space symbol). The resulting values indicate the probability of the logistic regression model selecting the appropriate language for a word based on the CLOUD representations at a specific character. T-tests with Bonferroni corrections for multiple comparisons (0.05/11) were used to contrast probability scores across versions.

The last step was to simulate the results from the Flavian vocabulary learning experiment. The resulting data from the five learning blocks (measured in log probabilities) were modeled using linear growth curve analyses (GCA) for the recognition and production tasks, respectively. We included second-order orthogonal polynomials to reflect linear and quadratic changes across the blocks, using the version (i.e., MONO, SP-EN, SP-BQ) and condition (ES+ versus ES-) factors as fixed effects on all time-terms. The condition factor was deviation coded as -1 (ES-) and 1 (ES+). The version factor was reverse Helmert coded to first contrast the SP-EN and SP-BQ versions (coded as -1 and 1) and then contrast the bilingual (BIL) versions against the MONO version (coded as -2 and 2, respectively). We included the main effects and interactions of the time, condition, and version factors in the fixed effects but excluded any three-way interactions with time-terms from the GCA models. The final GCA models only converged with the by-run intercepts. Estimating the Bayes Factor for these models was not informative due to the small number of runs in each version.

Results

CLOUD Spanish LDT performance

An ANOVA comparing the LDT training dataset accuracy by version revealed no differences between the three versions ($F_{(2, 27)} = 1.716, p = 0.199$). Similarly, the Helmert contrast indicated no differences between the monolingual and bilingual versions ($p = 0.150$) or between the two bilingual versions ($p = 0.275$). The average accuracy achieved by the monolingual version was 85.3% (SD = 0.2), while the Spanish-Basque version averaged 85.3% (SD = 0.2), and the Spanish-English 85.2% (SD = 0.2). We calculated the mean and standard deviation achieved by 20 randomly initialized but untrained CLOUD models on the same LDT training set to compute the empirical chance level. These randomly initialized models averaged

49.7% (SD = 1.0) on the training set. We then contrasted each version's achieved accuracy against this empirical chance-level using a Wilcoxon test. The results indicated that all versions performed above the empirical chance level (all $p < 0.001$). Supplementary Figure 3 provides more detail and shows the word clouds for the monolingual and bilingual models after pre-training.

An ANOVA comparing the LDT test dataset accuracy by version indicated no differences between the versions ($F_{(2, 27)} = 0.612, p = 0.550$). Additionally, the Helmert contrasts between the monolingual and bilingual versions and both bilingual versions did not reach significance ($p = 0.585, p = 0.347$, respectively). The empirical chance-level performance for this task was 49.5% (1.5%). All versions performed significantly above this level (all $p < 0.001$, $BF_{10} > 100$). The monolingual versions averaged 77.3% (SD = 0.6), the Spanish-Basque 77.1% (SD = 0.7), and the Spanish-English versions 77.3% (SD = 0.6). Thus, the monolingual and bilingual versions demonstrated comparable LDT performance on both trained and untrained words.

Language organization in the CLOUD

The two main features of the CLOUD architecture are its unified orthographic lexicon and its distributed word representations. In a second step, we evaluated whether the hidden representations of the pre-trained models contained sufficient information for determining language category despite their unified structure. To test this idea, we obtained the hidden representations of every word in the test set while processing one character at a time. Half of the words served as input to a logistic regression model trained to decode each word's language category from the hidden representations at every possible character position. We then tested the logistic regression model's performance on the remaining half of the representations at each time

step. We repeated this procedure to compare the MONO and SP-EN versions on the Spanish-English dataset and the MONO and SP-BQ versions on the Spanish-Basque dataset. Figure 4 depicts the logistic regression's probability of selecting the correct language at every character position.

Figure 4. *Probability of selecting the correct language at every character position.*

Note. Shading indicates significance at the Bonferroni corrected level. Time-step 0 is the space symbol's representation, which is identical for all words in all the models. MONO = monolingual; SP-EN = Spanish-English bilingual; SP-BQ = Spanish-Basque bilingual; CI = confidence interval.

Surprisingly, the logistic regression models performed significantly above chance level (0.5) after just the first character in all versions of the CLOUD model and datasets ($p < 0.001$, $BF_{10} > 100$). This does not imply that performance was good at this time step, as the probability of selecting the correct language was about 0.55. In the Spanish-English dataset, the logistic regression had a higher probability of correctly selecting the language category from the SP-EN versions than the MONO versions after the third character ($p_{bonf} < 0.001$, $BF_{10} > 100$), and until the ninth character ($p_{bonf} < 0.001$, $BF_{10} > 100$). Interestingly, decoding was more accurate from the MONO version than the SP-EN version at the last time-step ($p_{bonf} < 0.001$, $BF_{10} > 100$). At the tenth character, the MONO versions had an average probability of selecting the correct language of 0.895, whereas the SP-EN versions averaged 0.858.

In the Spanish-Basque dataset, decoding was more accurate from the SP-BQ version than the MONO version from the third ($p_{bonf} < 0.001$, $BF_{10} > 100$) to the tenth character ($p_{bonf} < 0.001$, $BF_{10} > 100$). At the tenth character, the MONO versions had an average probability of selecting the correct language of 0.896, whereas the SP-BQ versions averaged 0.940. Regardless of the differences between the bilingual and monolingual versions, these results suggest that, even in the MONO version, the internal representations of an unseen foreign word may be sufficiently different to distinguish whether it belongs to a known language or not (as opposed to identifying the exact language label of such word).

Flavian vocabulary learning in the CLOUD

Having matched the CLOUD models' performance after pre-training and evaluated the models' language organization, we focus on this study's central question. That is, how does exposure to words from two versus one language facilitate foreign vocabulary learning with varying degrees of orthographic similarity? Here is where the *dynamic* constraint becomes relevant. The pre-trained models learned the Flavian vocabulary, adjusting their weights to incorporate these novel words.

The results for the recognition task are shown in Table 3. The GCA indicated a significant effect of the linear and quadratic time-terms (both $p < 0.001$). The condition factor was also significant ($p < 0.001$), but the effect was opposite to that found in Study 1: words in the ES- condition overall had higher scores than those in the ES+ condition. As in Study 1, there were no differences between the bilingual versions ($p = 0.938$), but both bilingual versions outperformed the monolingual version ($p < 0.001$). The bilingual versions also had a significantly different linear slope than the monolingual version ($p = 0.036$). Finally, there was a significant interaction between condition and the monolingual versus bilingual contrast ($p = 0.007$). Contrary to Study

1, the difference between the monolingual and bilingual versions was greater in the ES- condition. There were no further two-way interactions (all $p > 0.05$). The CLOUD simulation results for the recognition task are depicted in Figure 5A.

Table 3. *Linear GCA of the simulated recognition learning task.*

Fixed Effects	Estimate	SE	df	t	p
(Intercept)	-24.175	0.073	27.0	-330.747	< 0.001
Linear	11.522	0.104	259.0	110.333	< 0.001
Quadratic	-0.708	0.104	259.0	-6.777	< 0.001
Condition	-0.196	0.047	259.0	-4.197	< 0.001
SPBQ-SPEN	-0.007	0.090	27.0	-0.079	0.938
MONO-BIL	-0.357	0.052	27.0	-6.899	< 0.001
Linear x Condition	-0.014	0.104	259.0	-0.133	0.894
Quadratic x Condition	-0.076	0.104	259.0	-0.724	0.470
Linear x SPBQ-SPEN	-0.216	0.128	259.0	-1.685	0.093
Linear x MONO-BIL	-0.156	0.074	259.0	-2.109	0.036
Quadratic x SPBQ-SPEN	0.150	0.128	259.0	1.175	0.241
Quadratic x MONO-BIL	-0.008	0.074	259.0	-0.105	0.916
Condition x SPBQ-SPEN	-0.103	0.057	259.0	-1.794	0.074
Condition x MONO-BIL	0.090	0.033	259.0	2.728	0.007
<i>Random Effects</i>	<i>Group</i>	<i>Variance</i>	<i>SD</i>	<i>Correlation</i>	
<i>Run</i>	(Intercept)	0.095	0.308		

Note. Significant fixed effect terms are highlighted in bold. SE = standard error; SD = standard deviation; SPEN = Spanish-English bilinguals; SPBQ = Spanish-Basque bilinguals; MONO = Spanish monolinguals; BIL = bilinguals.

The production task results are shown in Table 4 and depicted in Figure 5B. In this case, the analysis indicated significant linear and quadratic time-terms (both $p < 0.001$). Contrary to the recognition task, the condition effect was in the expected direction, with higher probabilities for ES+ than ES- words across all learning blocks ($p < 0.001$). There were no differences between the bilingual versions ($p = 0.723$), but both bilingual versions outperformed the monolingual version ($p < 0.001$). As in Study 1, there were linear by condition and quadratic by condition interactions (both $p < 0.001$), indicating that performance increased and reached an inflection point more rapidly in the ES+ than the ES- condition. Furthermore, there were linear and quadratic interactions with the bilingual versus monolingual contrast ($p = 0.047$, $p < 0.001$,

respectively). These interactions suggested a faster acquisition rate and earlier inflection point for the bilingual than the monolingual CLOUD versions. The rest of the two-way interactions were not significant (all $p > 0.05$).

Table 4. *Linear GCA of the simulated production learning task.*

Fixed Effects	Estimate	SE	df	t	p
(Intercept)	-110.461	0.251	27.0	-440.440	< 0.001
Linear	52.149	0.468	259.0	111.398	< 0.001
Quadratic	-17.372	0.468	259.0	-37.110	< 0.001
Condition	7.928	0.209	259.0	37.870	< 0.001
SPBQ-SPEN	-0.110	0.307	27.0	-0.358	0.723
MONO-BIL	-1.906	0.177	27.0	-10.750	< 0.001
Linear x Condition	-11.244	0.468	259.0	-24.019	< 0.001
Quadratic x Condition	4.157	0.468	259.0	8.879	< 0.001
Linear x SPBQ-SPEN	-0.280	0.573	259.0	-0.488	0.626
Linear x MONO-BIL	-0.662	0.331	259.0	-1.999	0.047
Quadratic x SPBQ-SPEN	0.072	0.573	259.0	0.125	0.901
Quadratic x MONO-BIL	1.420	0.331	259.0	4.290	< 0.001
Condition x SPBQ-SPEN	0.037	0.256	259.0	0.145	0.885
Condition x MONO-BIL	0.165	0.148	259.0	1.113	0.267
<i>Random Effects</i>	<i>Group</i>	<i>Variance</i>	<i>SD</i>	<i>Correlation</i>	
<i>Run</i>	(Intercept)	0.572	0.756		

Note. Significant fixed effects terms are highlighted in bold. SE = standard error; SD = standard deviation; SPEN = Spanish-English bilinguals; SPBQ = Spanish-Basque bilinguals; MONO = Spanish monolinguals; BIL = bilinguals.

Figure 5. *Study 1 simulation results.*

Note. Log-probabilities (symbols, vertical lines indicate $\pm 95\%$ confidence intervals) by version and condition for the recognition (A) and production (B) simulation tasks. The solid lines depict the average GCA model predicted values. The conditions are plotted separately to avoid cluttering. SP-EN = Spanish-English bilinguals; SP-BQ = Spanish-Basque bilinguals; MONO = Spanish monolinguals.

954 *Correlation with Study 1*

955 As a final exploratory step, we calculated the mean log probabilities achieved by all
956 CLOUD versions on each word by learning block and condition, separately for the recognition
957 and production tasks. We also computed average participant scores per word using the same
958 procedure. These values were subjected to a Pearson correlation to verify that the model
959 produced similar results to those achieved by participants for the same words and learning
960 blocks. The correlations were performed for the recognition and production tasks and each group
961 separately. The results are depicted in Figure 6. The results indicated that the recognition and
962 production scores were significantly and positively correlated (all $p < 0.001$), ranging from 0.77
963 to 0.86 in the recognition task and from 0.64 to 0.77 in the production task. These results were
964 expected considering that performance improved during the learning phase for the participants
965 and the model. Interestingly, overall, higher participant scores for a specific word in a learning
966 block corresponded to higher scores for that word in the simulations.

967

Figure 6. *By-item correlations between the simulation and participant scores.*

Note. Shading indicates the 95% confidence interval. Each shape is an individual observation. **(top)** Recognition task correlations. **(bottom)** Production task correlations. SP-EN = Spanish-English bilinguals; SP-BQ = Spanish-Basque bilinguals; MONO = Spanish monolinguals.

974 Summary

975 In Study 2, we introduced a computational model (CLOUD) to account for the findings
976 from Study 1. The CLOUD model is instantiated as a recurrent neural network with three
977 constraints: the resulting orthographic lexicon must be unified, distributed, and dynamic. We
978 have shown that this simple model can accomplish several feats. First, it can successfully
979 perform an adapted Spanish Lexical Decision Task without explicit instruction on word
980 meaning. Second, it can learn distributed representations of the orthotactic patterns in words
981 from different languages, which contain information about a word's language category. Third,
982 the CLOUD model partially replicated the results from Study 1, showing an advantage for
983 bilingual exposure and distinguishing between orthographically similar and dissimilar Flavian
984 words. Curiously, the recognition results showed that the effect of orthographic similarity went
985 in the opposite direction to that found in the behavioral experiment. If the ES+ words had also
986 been more similar to one another, the CLOUD model might have had a more challenging time
987 disentangling their representations to predict the appropriate label. Regardless, the recognition
988 and production simulation results corroborated the finding that experience with the orthography
989 of two languages facilitated learning orthographically similar and dissimilar words compared to a
990 single language.

991

992 Discussion

993 The present study explored how orthographic similarity and bilingual experience
994 influence foreign vocabulary learning by using complementary behavioral and computational
995 approaches. In Study 1, we showed (1) that words with orthographies that are more similar to a
996 known language are learned more accurately, (2) that bilingual individuals outperformed their

monolingual peers, and (3) that this bilingual advantage for vocabulary learning seems to be largely independent of orthographic similarity. Study 2 introduced a computational model of the orthographic lexicon for written vocabulary learning. Among other findings, the model reproduced the bilingual advantage for vocabulary learning and orthographic similarity effects observed in the behavioral results of Study 1. Here, we discuss how the CLOUD model's unique constraints—namely its unified, distributed, and dynamic nature—could account for the behavioral data.

All orthographic word forms are stored in a unified lexicon in the CLOUD model, regardless of the language. While we are not the first to propose the idea of an integrated mental lexicon (e.g., Baxter et al., 2021; French & Jacquet, 2004), the findings presented here suggest that this constraint is essential for understanding native and foreign vocabulary learning. Using a unified lexicon means information can be reused during vocabulary learning, increasing efficiency. For instance, this makes it unnecessary to construct completely different representations for the words “model” and “modelo”, since information related to one word supports acquiring the other. This may seem trivial, but the most prominent computational models of the mental lexicon have largely overlooked vocabulary learning, opting to implement whole-word or language-specific tags (Dijkstra et al., 2019b; Dijkstra & van Heuven, 2002). In the CLOUD architecture, words can share orthographic representations so long as they share the same script.

We have demonstrated that a unified orthographic lexicon facilitates learning orthographically similar words. As shown in Study 1, participants' performance was better on orthographically similar words in both the recognition and production tasks. The model reproduced the orthographic similarity effects in the production task. However, there were some

discrepancies in the recognition task. Aside from the different learning trajectories arising from the distinct nature of the behavioral and simulation tasks, perhaps the most relevant difference was the inverse effect of orthographic similarity found in the recognition task. A possible explanation is that, while orthographically similar words are more straightforward to produce, it is more difficult to disentangle their representations so as to assign a label (see also Supplementary Figure 4). Previous research has suggested that, for language learners, similarity can also produce interference rather than facilitation in the absence of cues that direct attention to the differences between words (Baxter et al., 2021; Nation, 2000). These discrepant findings provide testable predictions regarding the interplay of attention and word form similarity during receptive vocabulary learning.

The second constraint characterizing the CLOUD model is the use of distributed representations. Distributed representations allow the model to learn from the orthographic patterns composing words from different languages. Despite the unified lexicon, the results show that in this bottom-up model distributed representations can store information about a word's language category without the need for top-down language tags. While theory suggests that top-down signals can modulate language activation in the bilingual mental lexicon (Dijkstra & van Heuven, 2002; Grainger et al., 2008; Van Heuven et al., 1998), word form representations are still sufficient to distinguish language category. In other words, individuals do not need to constantly check the language of every word they read, as this information can be inferred from the word itself if necessary. These results are consistent with a growing literature investigating written language identification in bilingual contexts (e.g., Casaponsa et al., 2014, 2015). In brief, these studies suggest that bilinguals can identify the language of a word using the orthotactics of their known languages. Thus, like the CLOUD model, these studies indicate that orthographic

1043 information is sufficient to organize languages within the mental lexicon (Casaponsa et al., 2014,
1044 2015).

1045 Prior modeling efforts have shown that distributed representations in the bilingual lexicon
1046 can cluster by language (French, 1998; Li & Farkas, 2002), but our study extends these findings
1047 in several ways. First, we showed that language discrimination can occur at the orthographic
1048 level. Some orthographic patterns are found uniquely in words from specific languages (e.g.,
1049 “th” in English; “tx” in Basque); our model seems to capture such patterns in its distributed
1050 representations. Second, we showed that language separation is not a unique feature of the
1051 bilingual lexicon but rather a by-product of distributed representations. Even in the monolingual
1052 version, representations allowed the model to distinguish between words that did or did not
1053 belong to the known language, without any need to learn words from other languages. Third, the
1054 results suggest that as a word’s length increases, so does its individuality within the mental
1055 lexicon, such that longer words have more language-specific representations than shorter words.
1056 Finally, the model produced a “bilingual advantage” for language classification. Representations
1057 in bilingual versions of the model provided more information that was relevant for identifying
1058 languages than representations in the monolingual version, a difference that was more evident
1059 with shorter words.

1060 This study’s central finding is a bilingual advantage for foreign written vocabulary
1061 learning, evidenced in both human and model performance, receptive and productive vocabulary
1062 tasks, and orthographically similar and dissimilar words. Studies have shown that bilinguals
1063 outperform monolinguals when learning dissimilar words (Kaushanskaya & Marian, 2009a,
1064 2009b), but our results indicate that this is also the case for similar words. The results from Study
1065 1 are consistent with the idea that bilingualism enhances orthographic and/or lexical-semantic

networks, as suggested by prior research (e.g., Hirosh & Degani, 2018; Kaushanskaya & Marian, 2009b). However, we argue that such ad hoc explanations are not sufficient, in part because they offer no theory to explain how this strengthening/enhancement occurs or how biological neural networks might implement it. In Study 2, we offered an alternative explanation, demonstrating that a simple computational model that learns orthotactics from words in one or two languages could replicate the findings from Study 1. In the CLOUD model, experience with words from two languages shapes the distributed representations, making the lexicon less tuned to specific, restricted orthographic patterns. Interestingly, the effects were evident for both bilingual versions of the model, regardless of the language combination, pointing to bilingual exposure per se as the source of the advantage. We suggest that experience with two languages does not enhance or strengthen these networks but instead acts as a form of *regularization*.

Regularization is a common concept in cognitive and computational learning theories (e.g., Ferdinand et al., 2019; Girosi et al., 1995; Hudson Kam & Newport, 2005). In computational terms, regularization implies imposing sparsity or strength constraints (through penalty terms or data variability) on a model's representations to reduce generalization errors (Goodfellow et al., 2016). In humans, this process typically refers to how learners adapt their representations to reduce entropy in the information they process (Hudson Kam & Newport, 2005). Critically, we have demonstrated that this regularization process occurs even at the sub-lexical level when information on orthographic patterns is less predictable because it comes from two distinct languages. Thus, in Study 2, distributed orthotactic representations became less tuned to a specific language, due to more variable and unpredictable statistics, and were generally more flexible in accommodating the novel artificial vocabulary.

The final and possibly the most controversial constraint in the CLOUD model is its dynamic lexicon, by which learning a new word modifies the representations of existing words in the lexicon (see Supplementary Figure 4 for an example). It is safe to assume that the human brain never turns off its learning mechanisms, as evidenced by implicit learning studies (Christiansen, 2019; Perruchet & Pacton, 2006). Thus, it would make sense that language context and environmental demands continually modify existing representations. This constraint poses additional questions regarding the stability of the mental lexicon, particularly in adulthood. For example, do the representations of some words stabilize? If so, how much exposure is necessary to produce a change? Research suggests that, even in adult monolinguals, foreign language learning experience can reshape native language knowledge (Bice & Kroll, 2015). Furthermore, adult monolinguals exposed to heterogeneous linguistic contexts show a vocabulary learning advantage over those from a more homogeneous linguistic contexts (Bice & Kroll, 2019). Together, these findings suggest that the mental lexicon is not static, and mere exposure to different words forms can affect language processing and foreign vocabulary learning. The extent to which the mental lexicon is dynamic is an important question for future studies.

There are, of course, limitations when comparing a simple model like CLOUD to the complexity and nuance of human behavior. In our simulations, we did not model differences arising from early versus late second language learning. Instead, we approximated an adult monolingual and bilingual lexicon using exposure to random words in one or more languages as a proxy. In practice, bilingualism involves many more factors beyond exposure, ranging from individual learning experiences to culture and identity. Additionally, most mental lexicon theories posit a resting level of word activation (established in relation to the frequency of exposure to specific words) and suggest that this crucial factor intervenes in processes such as

1111 competition during word recognition (Baxter et al., 2021). In pre-training the CLOUD models,
1112 we just assumed that all words were equally frequent. While the influence of both second
1113 language age of acquisition and word frequency could easily be put to the test by modifying the
1114 CLOUD model's pre-training datasets (e.g., using complete texts rather than single words), these
1115 aspects remain beyond the scope of this study.

1116 It is important to note that we explicitly avoided meaning representations, opting to
1117 identify the minimal structure that could account for written vocabulary learning. This means
1118 that no distinction was made between cognates (e.g., "pera"-“pear”) and false friends (e.g.,
1119 “carta”-“letter” and not “card”) in the CLOUD model. Meaning representations have been
1120 consistently problematic to implement computationally. Some authors reduce them to manually
1121 coded distributed representations, and others treat them as localist (single-valued) labels (French
1122 & Jacquet, 2004; Laszlo & Plaut, 2012). Recent advances in artificial intelligence suggest that
1123 meaning representations are dynamic and highly context-dependent, like the orthographic
1124 representations in the present work (Devlin et al., 2019). Meaning representations pose an
1125 additional challenge when dealing with multilingual data. For instance, is the meaning of two
1126 words precisely the same across languages? Is word meaning even the same for two individuals?
1127 While it will be helpful for future work to explore the possibility of extending the CLOUD
1128 model by adding meaning representations, our aim here was to report the efficacy of a minimal
1129 model for learning orthographic representations in multiple languages.

1130 Finally, we do not claim by any means that the learning mechanisms employed by
1131 artificial neural networks are human-like or biologically plausible. Other models employing
1132 distinct learning mechanisms or architectures that produce unified, distributed, and dynamic
1133 representations could match or surpass the CLOUD model's capacity to explain our behavioral

data. Still, this model provides a first large-scale attempt at understanding the role of prior experience on foreign written vocabulary learning. Future work could employ more biologically plausible architectures to corroborate the ideas presented here, possibly also including phonological and meaning representations.

Conclusion

Foreign vocabulary learning is a multi-faceted and complex process influenced by many variables. Among these, past research has highlighted similarity and bilingual experience as catalysts for foreign vocabulary learning. The present study jointly tests and unifies these seemingly disparate findings under a common computational framework, whereby distributed representations of word forms are stored in a unified space and dynamically modified by orthographic learning experiences. Our model simulated human behavior to a large extent, corroborating the influence of orthographic similarity and showing a bilingual advantage for both receptive and productive vocabulary. Our results have important implications for how consistent experience with specific words in different linguistic contexts can influence foreign vocabulary learning.

Acknowledgments

This work has received funding from “la Caixa” Foundation and from the European Union’s Horizon 2020 research and innovation programme under the Marie-Skłodowska-Curie grant agreement no. 713673, personal fellowship code LCF/BQ/IN17/116200154004, and by the European Molecular Biology Organization (EMBO, Short-Term Fellowship code 8742), awarded to JAA. MC was supported by the Basque Government through the BERC 2018-2021 program and by the Spanish State Research Agency through BCBL Severo Ochoa excellence accreditation SEV-2015-0490 and project RTI2018-093547-B-I00. We also thank Prof. James Magnuson for reviewing and commenting on a former version of this manuscript.

Competing interests statement

The authors declare no competing financial, commercial, or institutional interests.

CRedit author contribution statement

JAA: Conceptualization, Methodology, Software, Investigation, Resources, Data Curation, Formal analysis, Writing – Original Draft, Visualization, Project administration, and Funding acquisition **AT:** Methodology, Formal analysis, Software, Writing – Review & Editing, Supervision **MZ:** Methodology, Formal analysis, Software, Writing – Review & Editing, Supervision **MC:** Conceptualization, Methodology, Writing – Review & Editing, Supervision, Project administration, and Funding acquisition.

Open Practices Statement

The anonymized participant information, behavioral and simulation data, and the code for the experimental tasks and statistical analyses are freely available at <https://osf.io/8534h/>. This experiment was not preregistered. The code for implementing the CLOUD architecture and simulations, including the data and helper functions for training and plotting the results, are freely available at <https://github.com/JoseAAManzano/CLOUD>.

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Appendix

Appendix 1. Language profiles and group contrasts in Study 1.

	Spanish Monolinguals		Spanish-Basque Bilinguals		Spanish-English Bilinguals		ANOVA			Helmert contrasts p-value	
	<i>M</i>	<i>SD</i>	<i>M</i>	<i>SD</i>	<i>M</i>	<i>SD</i>	$F_{(2, 117)}$	<i>p</i>	BF ₁₀	MONO-BIL	SPBQ-SPEN
Age	20.4	2.1	21.5	2.6	21.0	2.5	2.242	0.111	0.501	0.064	0.326
Non-verbal IQ	102.9	5.2	103.2	5.7	102.9	4.2	0.036	0.965	0.082	0.909	0.809
Education Level (1-6)	3.3	0.7	3.6	1.0	3.6	1.0	1.149	0.320	0.204	0.133	0.901
SES - Parental Education (1-6)	3.4	1.4	3.6	1.3	3.5	1.6	0.179	0.836	0.092	0.652	0.696
Age of Acquisition L1 ^a	0.0	0.0	0.0	0.0	0.0	0.0	-	-	-	-	-
Total Exposure L1 (%)	91.2	8.1	60.9	10.1	64.8	9.9	123.029	< 0.001	> 100	< 0.001	0.068
Self-rated proficiency L1 (1-10)	9.8	0.5	9.8	0.2	9.9	0.3	2.425	0.093	0.368	0.059	0.273
BEST L1 (0-65)	64.7	0.6	64.5	0.9	64.8	0.5	1.892	0.155	0.376	0.714	0.059
Age of Acquisition L2	5.3	1.6	3.0	1.8	3.5	1.7	19.809	< 0.001	> 100	< 0.001	0.196
Total Exposure L2 (%)	8.4	7.9	34.4	11.1	33.4	9.3	94.713	< 0.001	> 100	< 0.001	0.641
Self-rated proficiency L2 (1-10)	4.3	1.8	8.4	1.2	8.1	0.8	121.22	< 0.001	> 100	< 0.001	0.227
BEST L2 (0-65)	23.1	13.7	56.2	7.4	55.9	4.3	166.745	< 0.001	> 100	< 0.001	0.867
LexTALE L1 (%)	-	-	92.3	5.1	93.3	6.8	-	-	-	-	0.442 ^b
LexTALE L2 (%)	-	-	89.7	5.5	88.8	5.9	-	-	-	-	0.510 ^b

Note. Significant contrast terms are highlighted in bold. SD = standard deviation; MONO = Spanish monolinguals; BIL = bilinguals; SPEN = Spanish-English bilinguals; SPBQ = Spanish-Basque bilinguals; SES = socioeconomic status.

^a Statistic and *p*-value undefined due to zero variance.

^b Difference calculated using Welch t-tests.

Appendix 2. Recognition test GLMM results from Study 1.

Fixed Effects		Estimate	SE	z	p	BF ₁₀
(Intercept)		2.296	0.109	21.007	< 0.001	-
Day		-0.022	0.043	-0.516	0.606	0.048
Condition		0.063	0.029	2.144	0.032	0.439
SPBQ-SPEN		-0.027	0.126	-0.215	0.830	0.046
MONO-BIL		-0.142	0.073	-1.950	0.051	0.301
Day x Condition		0.003	0.029	0.113	0.910	0.001
Day x SPBQ-SPEN		-0.048	0.047	-1.025	0.306	0.003
Day x MONO-BIL		0.012	0.026	0.466	0.641	0.015
Condition x SPBQ-SPEN		0.043	0.037	1.158	0.247	0.004
Condition x MONO-BIL		-0.003	0.020	-0.151	0.880	0.014
<i>Covariates</i>						
Age		-0.108	0.044	-2.440	0.015	0.712
Non-verbal IQ		0.006	0.009	0.650	0.516	0.263
Gender		0.106	0.290	0.365	0.715	0.047
OSPAN score		0.012	0.007	1.703	0.089	0.954
<i>Random Effects</i>		<i>Group</i>		<i>Variance</i>		
<i>Participant</i>		<i>(Intercept)</i>		<i>SD</i>		
		Day		0.09		

Note. Significant fixed effects terms are highlighted in bold. SE = standard error; SD = standard deviation; SPEN = Spanish-English bilinguals; SPBQ = Spanish-Basque bilinguals; MONO = Spanish monolinguals; BIL = bilinguals.

Appendix 3. Production test LMM results from Study 1.

Fixed Effects	Estimate	SE	df	t	p	BF ₁₀
(Intercept)	13.552	0.434	111.2	31.205	< 2e-16	-
Day	-0.428	0.057	115.0	-7.514	0.000	> 100
Condition	1.486	0.116	115.0	12.782	< 2e-16	> 100
SPBQ-SPEN	-0.594	0.502	111.0	-1.183	0.239	0.075
MONO-BIL	-0.968	0.293	111.1	-3.303	0.001	3.033
Day x Condition	0.019	0.046	117.0	0.424	0.672	0.008
Day x SPBQ-SPEN	-0.089	0.070	115.0	-1.271	0.206	0.003
Day x MONO-BIL	-0.037	0.040	115.0	-0.910	0.365	0.048
Condition x SPBQ-SPEN	0.201	0.143	115.0	1.403	0.163	0.005
Condition x MONO-BIL	0.124	0.082	115.0	1.513	0.133	0.158
<i>Covariates</i>						
Age	-0.366	0.176	111.0	-2.080	0.040	0.050
Non-verbal IQ	-0.031	0.035	111.0	-0.904	0.368	0.004
Gender	1.225	1.154	111.0	1.062	0.291	0.216
OSPAN score	0.043	0.029	111.0	1.474	0.143	0.016
<i>Random Effects</i>	<i>Group</i>	<i>Variance</i>	<i>SD</i>	<i>Correlation</i>		
Participant by Condition	(Intercept)	2.690	1.640			
Participant	(Intercept)	16.978	4.121			
	Day	0.134	0.366	0.15		

Note. Significant fixed effects terms are highlighted in bold. SE = standard error; SD = standard deviation; SPEN = Spanish-English bilinguals; SPBQ = Spanish-Basque bilinguals; MONO = Spanish monolinguals; BIL = bilinguals.

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