

Beetle: A Bilingual Model Suite for Modelling Second-Language Processing

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Abstract

Bilingual language models (LMs) offer a controlled setting for studying how training conditions shape second-language (L2) behaviour, but prior work typically varies exposure structure, scale, and architecture at once, making it difficult to attribute effects to any single factor. We introduce Beetle, a controlled language model pretraining framework in which tokeniser, target language, training budget, and exposure structure are each independently manipulable, enabling systematic and comparable experimentation of training conditions. Using Beetle, we train and release 285 bilingual and 45 monolingual open-source LMs with rich checkpoints across a range of exposure schedules, data scales and first languages (L1s) to study multilingual pretraining and computational modelling of bilingualism and second language learning. Evaluating models on human bilingual and second language reading-time prediction and grammaticality judgement tasks, we find that staged and temporally structured curricula consistently improve alignment with language learner reading time compared to balanced bilingual training, with the largest gains at smaller data scales and for typologically closer language pairs. The Beetle models are well suited tools to help move computational psycholinguistics beyond its prevailing monolingual, English-centric focus toward models of human bilingual processing, to study cross-lingual learning dynamics, while supporting community-based development of controlled model families.

🐞 beetlelm.github.io

1 Introduction

In contrast to multilingual models, bilingual and second-language (L2) language models (LMs) are models trained on exactly two languages, either jointly or in sequence. These models are a useful middle ground between monolingual and mas-

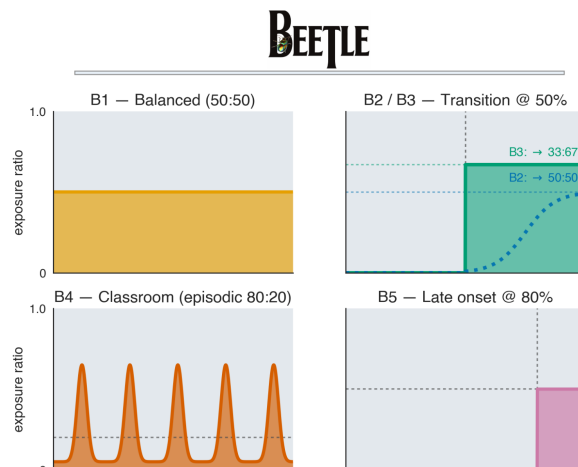


Figure 1: Beetle is an open-source language model pretraining framework. We use it to study bilingual and multilingual language acquisition in language models under tightly controlled experimental conditions. Each facet represents different **data curricula** of different first languages and English introduced in different proportions and stages of pretraining. Our paper uses five curricula (B1–B5) to model different human bilingual and second-language learning scenarios.

sively multilingual systems for studying multilingual language model pretraining. They also allow us to study bi- and multilingual language acquisition, representations, interpretability, and learner simulation (Frank, 2021; Yadavalli et al., 2023; Oba et al., 2023; Aoyama and Schneider, 2024; Constantinescu et al., 2025; Arnett et al., 2025). However, important questions about the dynamics of bilingual training remain open. When does cross-linguistic transfer emerge during pretraining, how does transfer depend on typological similarity, relative timing and distribution of exposure to each language, and how does joint training compare with learning each language independently (Chang et al., 2022; Blevins et al., 2022; Wang et al., 2024a; Rajaei and Monz, 2024; Körner et al., 2026; Zhou et al., 2026)? Existing bilingual models provide useful evidence for transfer,

but are often constrained by available training setups. The only open bilingual family with checkpoints, B-GPT (Arnett et al., 2025), was developed for only a limited set of language pairs and does not provide fine-grained checkpoints over the early stages of training, making it difficult to distinguish effects that emerge during initial acquisition from those that arise later in training. Moreover, the absence of matched monolingual baselines makes it difficult to determine whether apparent bilingual benefits reflect genuine transfer between languages or simply differences in the amount and composition of training data. These limitations motivate controlled bilingual pretraining experiments that vary exposure structure while tracking learning from the earliest stages and comparing bilingual models against matched monolingual controls.

Despite the fact that most people speak at least two languages (Grosjean, 2021), most cognitive science research focuses on monolingual language processing. In computational cognitive science, one limitation has been the lack of available bilingual language models. Additionally, the studies that have been done differ significantly in training scale, exposure schedule, language pair, continual-learning mechanism, and evaluation protocol. As a result, it is hard to attribute behaviour of a model to any single training decision.

To address this, we introduce Beetle, a modular LM pretraining and analysis framework that controls data exposure, alongside the usual choices of data quantity, tokeniser, and architecture (§3), to compare and investigate these confounding factors. We unify previously proposed methods in our training framework. and use our models to investigate whether acquisition-inspired language exposure curricula during bilingual LM pretraining leads to better alignment with metrics of human language processing.

Using our training framework, we train a suite of **285 bilingual models** spanning 21 L1s, holding architecture, model size, tokenizer, and overall language mixture fixed. We vary two factors: the L1 (English is always the L2) and the order in which the two languages are presented during pretraining. We train bilingual models with 5 exposure conditions at three FineWeb dataset scales (100M, 2B and 24B tokens), plus a matched human-scale 100M condition. We additionally provide **45 monolingual baselines covering 20**

languages. Every Beetle model is released with its full checkpoint trajectory for studying cross-lingual learning dynamics.

We find that structured exposure improves alignment with human eye-tracking reading times on Multilingual Eye-movement Corpus (MECO) L2 data (Kuperman et al., 2023, 2025) and that ordered curricula tend to outperform fully interleaved training, suggesting that gradual language introduction improves alignment with psycholinguistic data. These effects are not explained by differences in overall proficiency or language balance, and remain consistent across controlled ablations. We additionally evaluate larger massively multilingual models, showing that carefully designed bilingual curricula can match or exceed L2 reading-time alignment under substantially smaller parameter budgets. These results demonstrate that the point during training when languages are introduced is a key determinant of how closely language models reproduce human second-language reading behaviour.

Beyond reading time, we further probe bilingual processing through cross-lingual structural priming (§6.1) and CEFR-stratified L2 learner-error discrimination on BLiSS (§6.2), and find that curriculum effects do not transfer uniformly across these tasks: balanced exposure is often competitive or better on grammaticality and error discrimination even where staged curricula best predict reading times.

The primary contributions of this paper are 1) a flexible training framework to enable controlled multilingual pretraining with learning dynamics 2) a suite of bilingual LMs 3) and modelling efforts for bilingual data on two evaluation domains, which can inform future bilingual cognitive modelling work.

2 Background

Bilingual models. Bilingual and second-language language models (L2LMs) offer a controlled middle ground between monolingual and massively multilingual models, and have been used to study second-language acquisition through measures such as reading times and structural priming (Matusevych et al., 2013; Yadavalli et al., 2023; Oba et al., 2023; Aoyama and Schneider, 2024; Arnett et al., 2025; Constantinescu et al., 2025; Feng et al., 2026). But there is no single recipe for creating an L2LM: prior

work varies in what languages are seen, when they are introduced, and how strongly earlier knowledge is preserved. Some approaches train both languages jointly, while others introduce the L2 after L1 pretraining, using continual-learning methods such as elastic weight consolidation (EWC) to limit forgetting (Constantinescu et al., 2025). Others manipulate the timing and distribution of L1 and L2 exposure directly, as in the structured exposure regimes of B-GPT (Arnett et al., 2025). This heterogeneity makes it difficult to disentangle effects of language pair, model scale, and exposure history. Our framework adopts this structured-exposure approach while systematically controlling these factors, enabling reproducible comparisons across bilingual training curricula.

Modelling human language processing. Within psycholinguistics, LM surprisal is often used to model processing difficulty. Surprisal is incorporated as a regression predictor alongside baseline lexical covariates, and evaluated via the improvement in log-likelihood over this baseline ($\Delta \log L$; Smith and Levy, 2013; Wilcox et al., 2020; Oh et al., 2022; de Varda and Marelli, 2023), making psychometric predictive power dependent on how well a model’s probability distribution aligns with human reading behaviour rather than on raw model quality alone. However, while LM–human alignment has been studied extensively in L1 settings, bilingual and L2 reading-time modelling remains comparatively under-represented (Frank, 2014; de Varda and Marelli, 2022; Aoyama and Schneider, 2024), and this gap is especially pronounced in controlled large-scale sweeps of training conditions. In this paper, we hope to help address these limitations in the literature.

3 The Beetle Training Framework

Beetle is a language model pretraining framework that allows controlled manipulation of pretraining conditions. We apply Beetle for controlled pretraining of variables that prior L2LM work has manipulated separately: L2 onset timing, L2 exposure ratio, and continual-learning regularisation. Language exposure in bilingual pretraining is modelled as changing continuously over the course of training, making it possible to represent gradual or abrupt transitions between languages, periodic bursts of exposure, and clustered context-

dependent input.

Architecture. The default backbone, **PicoDecoder** (Diehl Martinez et al., 2025), is a 125M-parameter LLaMA-style causal decoder (Touvron et al., 2023): 14 layers, $d_{\text{model}} = 768$, 12 attention heads with one KV head (grouped-query attention), Rotary Position Embeddings, SwiGLU activations, RMSNorm, sequence length 512. This places Beetle on a contemporary LLaMA-class architecture (RoPE, SwiGLU, RMSNorm, grouped-query attention) that mirrors the components used in current open-weight LLMs, rather than the GPT-2-style decoder used in B-GPT (Arnett et al., 2025) and the embedding-and-head adaptation of Aoyama and Schneider (2024). Full training hyperparameters are listed in Table 4.

Beetle also contains modular logic for tokenization, potentially allowing investigation of the benefits of vocabulary overlap, different tokenization schemes (e.g., SentencePiece, UnigramLM, SuperBPE, BPE) and equal compression (Kallini et al., 2025). Our models use a BPE tokenizer based on the Huggingface tokenizers library, with a 50K vocabulary. The Beetle models have tokenizers are trained with equal compression, so they have the same compression rate in both languages. This means each model see the amount of information for each language in each sequence.

Exposure curricula. We compare five exposure curricula that manipulate how L2 input is distributed over training. Four curricula differ primarily in when L2 is introduced and how the L1:L2 mixture subsequently changes; B4 instead keeps L2 available throughout training but varies when the model sees L2 tokens, concentrating them into discrete episodes. The curricula therefore vary in L2 onset, final L1:L2 ratio, and temporal distribution, and are illustrated in Figure 1 (see section A.1.2 for details). We report the total proportion of training tokens in L2 for each curriculum, since curricula that introduce L2 at different points necessarily provide different amounts of L2 unless their later exposure compensates for the delayed onset.

- **B1 (Balanced):** L1 and L2 are presented throughout training in an approximately constant 50:50 mixture. Both L1 and L2 are continuously available from the beginning of training, with equal relative exposure throughout training.

- **B2 (Simultaneous):** Models are trained on L1 only for the first 30% of training. After this, L2 is gradually introduced using a sigmoid transition, where both languages are sampled in varying proportions (with periods of L1-dominance, L2-dominance and L1 re-exposure). For the final period of training (85 – 100% of training steps), the L1 and L2 are in a 50:50 mixture. L2 comprises 25% of all training tokens.
- **B3 (Sequential):** Training begins with L1 only for the first third of training. From 30 – 50% of training steps, L2 is gradually introduced using a sigmoid transition, eventually reaching an L2-dominant data mixture. L2 accounts for 33.5% of all training tokens.
- **B4 (Episodic):** Unlike B2, B3, and B5, L2 is available throughout training rather than being introduced at a specific onset. The overall L1:L2 ratio is 80:20, but L2 tokens are temporally clustered into intermittent, high-variance episodes rather than being evenly distributed. B4 tests the effect of *when L2 tokens occur within training* while keeping L2 available from the outset. L2 is 20% of training tokens. It represents learning scenarios where language learners have “bursty” increases in exposure.
- **B5 (Late):** B5 is a late-onset sequential curricula. It is similar to B3 with the sequential introduction of L2, but the L2 data is only introduced later in training. Training begins with L1 only for the first 50% of training. From 50 – 80% of training steps, a sigmoid transition then gradually increases L2 exposure to a L2-dominant data mixture. L2 tokens represent 10% of total training data.

4 Models & Training

We release **285 bilingual and 45 monolingual Beetle open-source language models** spanning **21 L1s**, with approximately 30 checkpoints per model. We train controlled bilingual models that independently vary the first language (L1), exposure curricula (B1 – B5) and data scale (100M, 2B, 24B tokens).

Beetle-Data. The human-scale models are trained on 100M tokens from BabyBabelLM (Jumelet et al., 2025a); the web-scale models (at

100M, 2B, 24B tokens) use FineWeb-2 (Penedo et al., 2025) for L1 and FineWeb-Edu for English. We implement a data decontamination pipeline, removed via 13-gram overlap detection following Brown et al. (2020a), for our 19 evaluation datasets (full list in subsection A.1.1). We release the full data tokenized in the order seen by the model for replicability and studying data memorisation.

L1s. Beetle models cover a typologically diverse set of L1s, with coverage continually expanding to support broader psycholinguistic and cross-lingual modelling. At 100M FineWeb, our experiments report results on Danish, German, Greek, Estonian, Basque, Filipino (Tagalog), Finnish, Hebrew, Hindi, Icelandic, Italian, Japanese, Korean, Dutch, Polish, Russian, Spanish, Turkish, and Chinese. At larger data scales, we focus on 9 L1s (German, Hindi, Italian, Dutch, Polish, Russian, Spanish, Turkish, Chinese). For BabyBabelLM, we report 100M-token experiments for German, Chinese, and Dutch.

Checkpointing Checkpoints are saved according to a $\log_2$ schedule following Pythia (Biderman et al., 2023), which re-starts at the beginning of each new exposure phase. This enables granular investigation of learning dynamic near phase boundaries, but with more sparse checkpointing during less critical periods of training. For each model, we release ≈ 30 checkpoints. Following Diehl Martinez et al. (2025), checkpoints save model gradients, activations and circuits, facilitating detailed interpretability analyses on circuit formation in bilingual LM pretraining (Inaba et al., 2025). To the best of our knowledge, our models will be the first with checkpoints available for several of these languages, enabling more linguistically diverse training dynamics research.

Baselines. We compare our models against two types of baselines. **Monolingual baselines** are matched-architecture Beetle models pretrained on a single language for German, Dutch and Chinese across all scales and Russian, Italian, Turkish and Basque at 100M/2B scale.

Massively Multilingual LLMs: we also compare Beetle models to massively multilingual base models, specifically, Apertus 8B (Swiss AI Initiative, 2025), XGLM 4.5B (Lin et al., 2022), Llama 3.1 1B (Grattafiori et al., 2024), Gemma 3 270M (Team et al., 2025), and Qwen 3 0.6B (Yang et al.,

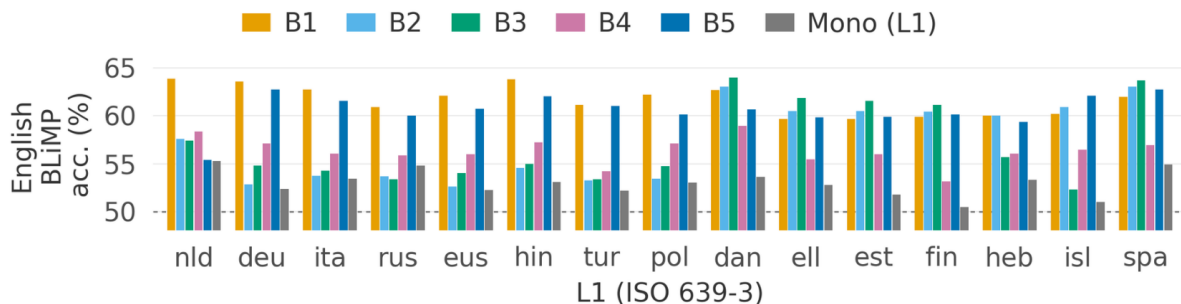


Figure 2: Beetle English BLiMP Accuracy for 100M FineWeb models across 15 L1s (Dutch, German, Italian, Russian, Basque, Hindi, Turkish, Polish, Danish, Greek, Estonian, Finnish, Icelandic and Spanish) and 5 exposure curricula. Full Monolingual and Multi-BLiMP accuracies for the Beetle models are in [Appendix E](#).

2025). Full baseline model details are given in [Table 8](#).

4.1 Analysing Curriculum-Induced Learning Dynamics

Before comparing our models with human behavioural data and metrics of bilingual language, we visualize the training dynamics ([Figure 3](#)) and test grammatical learning ([Table 7](#)) in order to validate that the exposure curricula demonstrate expected patterns. In order to avoid confounds from tokenizers or writing systems ([Yang et al., 2026](#)), we calculate the sentence-level negative log-likelihood (Sent-NLL) for each parallel item in FLORES-200 and calculate the mean ([Chang et al., 2024](#)). This provides a comparable metric of model performance across languages and across models.

Cross-Lingual Transfer and L1 Retention

The FLORES-200 trajectories in [Figure 3](#) reveal a strikingly asymmetric pattern of bilingual acquisition: introducing English causes an abrupt, curriculum-aligned increase in L1 sentence-level NLL, followed by partial recovery, while English NLL consistently declines after its introduction. Observed alignment of the shock is aligned with the L2 onset and subsequently recovers: L1 NLL increases under B2/B3, compared with the later-onset B5. NLL changes less under B4, where English ultimately accounts for only 20% of the mixture. Chinese and Hindi exhibit large disruptions than other languages, such as Dutch and German.

This divergence is consistent with a competition-for-capacity account of cross-lingual interference: acquiring a newly introduced language produces an immediate cost to the language already represented by the model, with the size of the cost depending strongly on the

exposure schedule ([Whitford and Titone, 2015](#)).

Mono- and Multi-BLiMP. We evaluate the Beetle models on monolingual BLiMPs (BLiMP ([Warstadt et al., 2020](#)) for English; BLiMP-NL ([Suijkerbuijk et al., 2025b](#)) for Dutch; ZhoBLiMP ([Liu et al., 2025b](#))) and MultiBLiMP ([Jumelet et al., 2025b](#)). [Figure 2](#) shows L2 English BLiMP scores across all L1s and curricula for 100M FineWeb Beetle models. Balanced exposure curricula (B1), where English is available throughout training, typically have higher L2 English BLiMP performance than staged bilingual curricula (B2 – B5), where L2 English is introduced later in training. However, for some (largely Germanic or Indo-European) L1s, some staged curricula can achieve comparable L2 performance. Detailed monolingual BLiMP and MultiBLiMP results for all data scales for the Beetle are reported in [Table 7](#).

5 Reading Time (MECO L2)

The study of language processing in multilinguals is still an emerging area in computational psycholinguistics. Beetle provides a way to manipulate model training curricula such that we can test hypotheses about how different patterns of learning shape model predictions; and thus may enable research into how different forms of language exposure may impact patterns of reading.

Data scale is also a relevant factor in modelling human language processing. Research suggests that improvements in models’ next-word prediction capability (as measured by perplexity) only lead to a better fit to reading times up to point, after which the alignment becomes worse ([Kuribayashi et al., 2021](#); [Wilcox et al., 2020](#); [Oh et al., 2022, 2024](#)). This transition has been reported

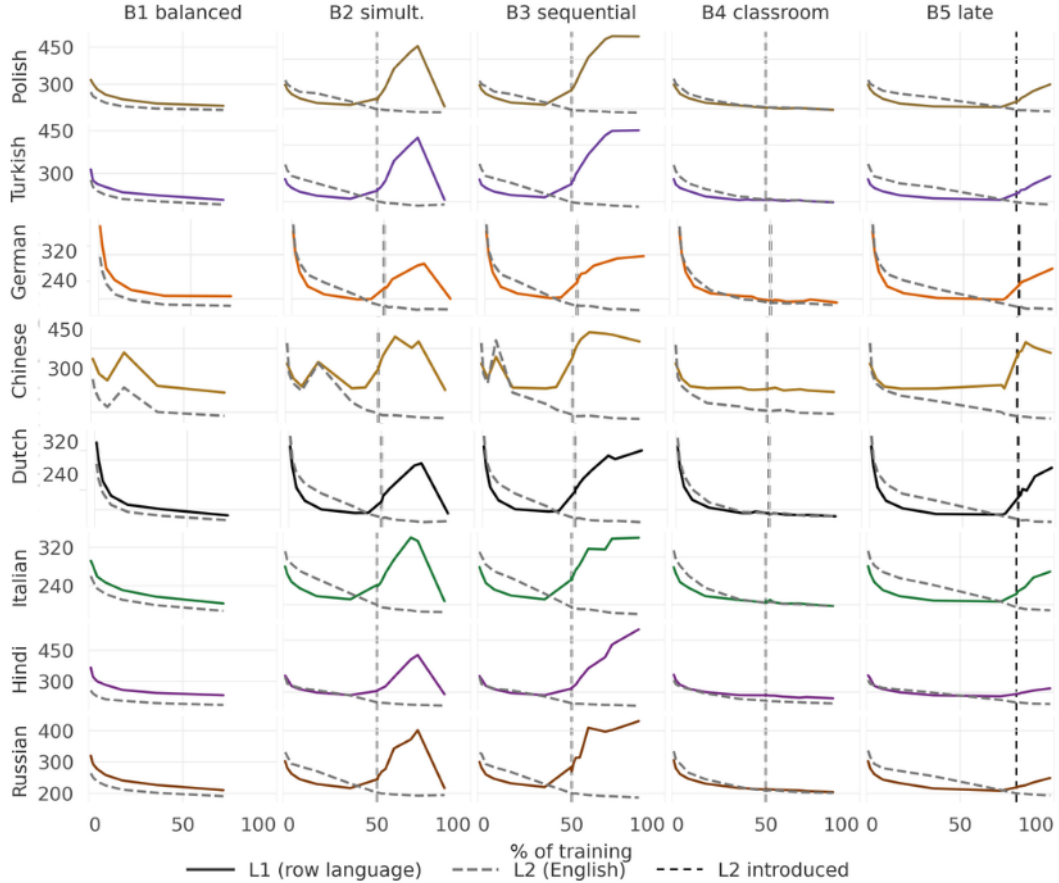


Figure 3: **FLORES Sentence NLL.** Each facet is one model; curves report mean sentence-level NLL in bits on 1,012 parallel FLORES-200 devtest sentences (lower is better), with solid lines for L1 and dashed lines for English. The vertical dashed line shows L2 English introduction.

to occur at around 2B training tokens (Oh and Schuler, 2023), with some variation depending on reading time measure or dataset (Aoyama and Wilcox, 2025; Michaelov and Bergen, 2026). Beyond this point, the fit to larger model surprisal degrades to a greater extent (Oh and Schuler, 2023; Michaelov and Bergen, 2026), which may explain why smaller models trained on large amounts of data often perform better than larger ones (Oh et al., 2022, 2024). Additionally, there is a movement to use “human-scale” pretraining data (~ 100 M tokens; Choshen et al., 2026) that is also developmentally plausible, composed of child-oriented data (Jumelet et al., 2025a). We compare both of these data scales against near-Chinchilla-optimal (Hoffmann et al., 2022) web-scale data (24B tokens for 125M parameter models).

MECO eye-tracking dataset. We evaluate how bilingual exposure curricula affect how well Beetle’s surprisal predicts human L2 reading times using the Multilingual Eye-Movement Corpus

(MECO), a multilingual eye-tracking benchmark covering controlled reading in typologically diverse languages (Siegelman et al., 2022, 2025; Kuperman et al., 2023, 2025). We focus on English L2 reading by Dutch, German, and Chinese L1 participants using the combined Wave 1+2 releases¹. MECO supports controlled cross-linguistic comparisons across matched reader populations. We use Beetle surprisals to predict *first-pass duration* (also known as *gaze duration*), a widely-studied psycholinguistic eye-tracking measure that represents the time spent fixated on a word in the first pass before moving to another word, which shows strong surprisal-based prediction effects (e.g., Wilcox et al., 2020), and in the multilingual processing literature has been associated with early lexical access and initial word integration during reading (Dussias, 2010; Luke et al., 2023; Nahatame and Uchida, 2025). We compare the Beetle models to other baseline LMs, selected

¹<https://meco-read.com/>

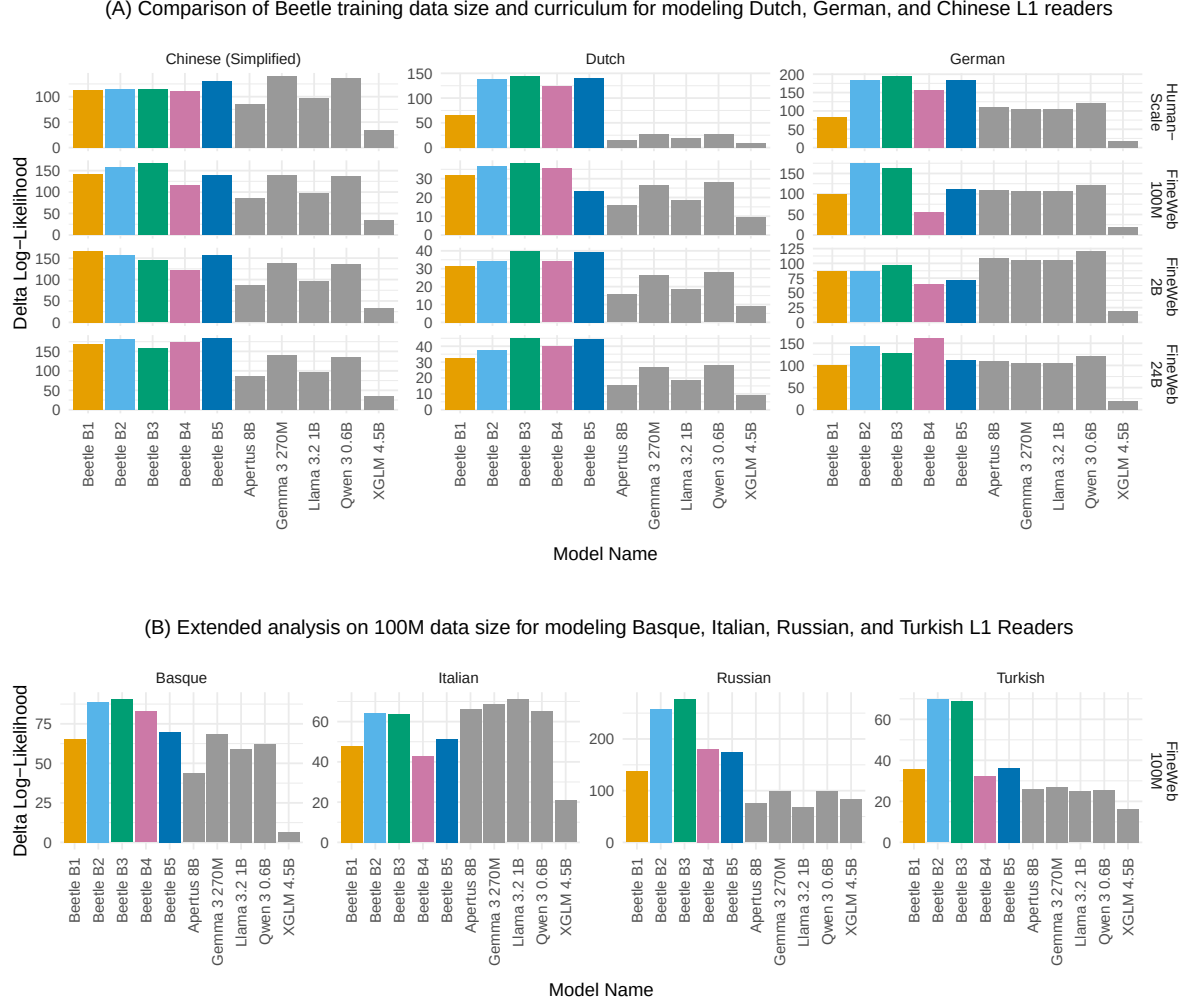


Figure 4: **Comparison of L2 Reading Time Alignment (MECO, (Siegelman et al., 2025; Kuperman, 2025)) of Beetle and multilingual LLMs** : (a) B1-B5 Dutch/Chinese/German-English Beetle (FineWeb 100M, 2B, 24B (Penedo et al., 2025), BabyBabelLM (Jumelet et al., 2025a)) and (b) B1 - B3 Basque/Italian/Russian/Turkish-English Beetle (100M FineWeb)

on the basis of being massively multilingual, and thus confirmed to or likely to be trained on the languages of interest. Given the aforementioned scaling effects, we select the smallest model of each family available. Mixed-effects regressions compare models with and without surprisal predictors, with improvements measured as $\Delta \log L$ (see Appendix C for full details).

Results First, we consider L2 reading time for Dutch-, German-, and Chinese-L1 models. For these language pairs, we use models trained on all five curricula and four dataset sizes and compare how well they predict reading time (Figure 4A). Figure 4 shows that the MECO alignment of the Beetle models is comparable to, or exceeds, multilingual LLMs at a range of parameter counts. Across seven L1s in Figure 4, staged exposure cur-

ricula (B2/B3/B5) consistently produce stronger surprisal-reading-time alignment than balanced bilingual exposure (B1); an effect strongest for Russian and German/Dutch L1s. Across training scales, effects of staged exposure are strongest for Dutch and German readers and weaker for Chinese readers, suggesting that curriculum benefits interact with typological proximity to English.

Comparing Human-Scale and FineWeb data at 100M token training budget, child-oriented training data from BabyBabelLM (Jumelet et al., 2025a) provides higher MECO alignment for Dutch and German L1 reading times, though this is not observed for Chinese L1 data. For Chinese, Dutch, and German, the models trained on 24B tokens show a closer fit than at the smaller data scales, which contrasts with previous research on

monolingual reading time showing a decrease in fit beyond 2B tokens (Oh and Schuler, 2023). Figure 4 shows reading time prediction for four additional L1s: Basque, Italian, Russian, and Turkish. For all language pairs except for Italian, surprisal calculated using our models better predict reading time than surprisal calculated with larger multilingual models.

6 Bilingual Processing Effects

6.1 Structural Priming

Previous work has argued that bilingual speakers share syntactic representations between languages. This allows for cross-linguistic syntactic priming: bilingual speakers are more likely to re-use the same syntactic structure in one language after hearing it in another language (Loebell and Bock (2003); Hartsuiker et al. (2004); Van Gompel and Arai (2018) i.a.). It has been demonstrated that language models also exhibit crosslingual structural priming, showing that language models also share crosslingual representations (Michaelov et al., 2023; Arnett et al., 2025).

Curr.	FineWeb		HumanScale	
	diff	p	diff	p
<i>Bernolet (genitive)</i>				
B1	1.051	.0004	1.369	<.0001
B2	0.991	.037	1.095	<.0001
B3	0.969	.051	1.216	<.0001
B4	1.252	.0008	0.565	.005
B5	1.075	.0003	0.571	<.0001

Table 1: Cross-Lingual Structural Priming of Dutch-English 100M (BabyBabelLM) and 2B (FineWeb) Beetle models. Difference in surprisal (nats) between congruent and incongruent primes using Arnett et al. (2025)’s structural priming measures.

We replicate the genitive priming (Bernolet et al., 2013) experiments in Arnett et al. (2025) with human-scale and web-scale Dutch-English Beetle models. Following Arnett et al. (2025), we quantify structural priming as the increase in the probability of producing a target sentence after a matching (congruent) prime compared with a mismatching (incongruent) prime. For each model–language pair, we fit a linear mixed-effects model with prime type as a fixed effect and experimental item as a random effect. We find the Beetle models, even when trained on smaller amounts of data (100M tokens), can show robust priming effects across curricula, similar to effects seen in

other bilingual models, such as the B-GPT models (Arnett et al., 2025) and larger multilingual models (Michaelov et al., 2023) (Table 1).

6.2 L2 Discrimination & CEFR

We secondly evaluate whether the curriculum effects observed in reading-time prediction also extend to grammatical discrimination. We use BLiSS (Gao et al., 2025), which tests whether models distinguish between a corrected sentence s_{corr} , a human learner error s_{lrn} , and an artificial error s_{art} . We measure sentence plausibility using bits per token (BPT),

$$\text{BPT}(s) = -\frac{1}{|s|} \sum_{t=1}^{|s|} \log_2 p(w_t | w_{<t}).$$

where lower BPT means that the model considers the sentence more likely. We report RP@0, the proportion of items for which the model assigns a lower BPT to the human learner error than to the corrected sentence, i.e., whether it prefers the learner error over the correction.

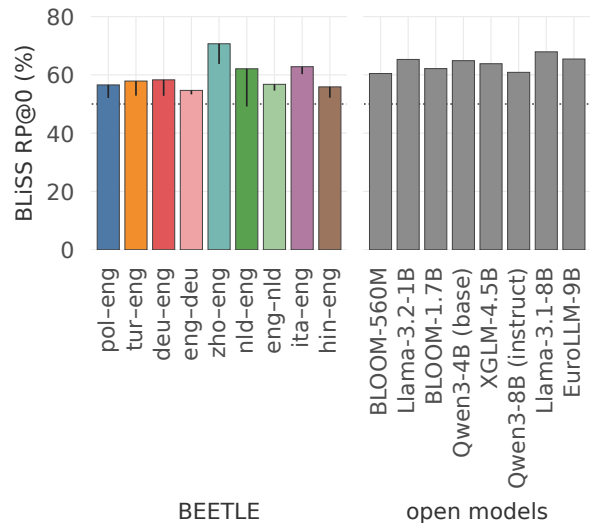


Figure 5: **BLiSS: Beetle vs. multilingual LLM performance.** Beetle models achieve comparable performance to multilingual LLM baselines. Detailed results are reported in subsection D.1.

On BLiSS, staged curricula (B2, B3-33, B5) generally outperform balanced exposure (B1), although the differences are smaller than those observed for MECO reading-time prediction (Fig. 5). BLiSS performance of Beetle models is comparable to larger multilingual LLMs (see Table 6 and Table 5 for more detailed results; and other CEFR-graded pedagogical results in Figure 7).

7 Discussion and Conclusion

Although psycholinguistics and cognitive science have historically focused on monolingual English-speaking, high-resource, and WEIRD populations (Majid and Levinson, 2010; Bylund, 2022), bilingualism and second-language (L2) processing are central to understanding human language processing. Computational approaches using language models inherit this bias, and an over-reliance on English and monolingual participants limits the generalisability of theories of language processing and acquisition (Blasi et al., 2022).

To address this gap, we introduced Beetle, a modular bilingual pretraining framework that disentangles exposure *structure* from training *scale* while holding architecture, tokeniser, and L2 target language fixed. Using Beetle, we pretrained 285 bilingual and 45 monolingual language models spanning 21 L1s and five exposure curricula, and we release checkpoints, training data, and reproducible pipelines to support future work on bilingual language modelling, learning dynamics, and cognitive modelling. Beetle provides interpretable and competitive models of bilingual processing. Small bilingual models trained under carefully controlled exposure conditions frequently matched or exceeded substantially larger massively multilingual systems on cognitively oriented evaluations, narrowing the gap between open-data academic models and closed-data industrial systems. Yet no single curriculum dominated.

Sequential and late-onset schedules produced stronger alignment with human L2 reading times, suggesting that temporally structured exposure better captures incremental bilingual processing, whereas balanced exposure achieved the strongest grammaticality (BLiMP) performance, indicating that more integrated exposure may better support robust grammatical generalisation; on BLiSS error discrimination the curriculum differences were smaller, with no single schedule dominating. That different schedules produce measurably different linguistic and cognitive behaviours, even with architecture and training volume held constant, suggests that carefully structured bilingual pretraining may yield stronger computational models of human language processing and language acquisition.

By releasing a reproducible framework alongside open bilingual models designed for study-

ing bilingualism and L2 acquisition, Beetle lowers the barrier to systematic research at the intersection of NLP, psycholinguistics, and cognitive science. We hope it will support future work using language models as experimentally controllable systems for investigating how language experience shapes processing, prediction, and acquisition across diverse linguistic settings.

7.1 Future Work

There are several features of the Beetle framework that we did not discuss in the paper, due to space limitations. We introduce them here and highlight their potential utility.

Trilingual and Multilingual Models. Beetle is designed for multilingual pretraining, not just for training bilingual LMs. It can be used to develop more complex exposure curricula for multilingual LM pretraining or trilingual language modelling

Alternative Architectures and Additional Manipulations. Following recent work investigating training dynamics across architectures (Michaelov et al., 2025), we implement encoder-decoder, MoE, and SSM architectures (described in App. A.1.2). Extending the analyses in this paper to other architectures could help us understand whether these effects are specific to transformer language models. Beetle additionally integrates a range of continual-learning strategies (parameter regularisation, replay, meta-learning, distillation, and architectural variants); the full registry and taxonomy are given in App. A.1.2 (Table 2, Table 3).

Training Dynamics. We trained models with rich checkpoints, but only did limited analyses of how the models changed over training across different curricula. Up to now, there have been very few models with checkpoints for any language other than English. Future work could investigate how consistent training dynamics are across languages.

Interpretability. PicoDecoder’s compatibility with Pico-Analyze (Diehl Martinez et al., 2025) allows mechanistic analysis of how bilingual pretraining manipulations affect weight geometry (e.g., shifts in effective rank or representational similarity) across checkpoints (Diehl Martinez et al., 2025; Inaba et al., 2025).

8 Limitations

L2-English. The Beetle pretraining experiments reported in the paper focus on non-English L1 data to English L2. Non-English L2s are not the focus due to limited evaluation metrics; this makes claims about directional asymmetries in transfer limited.

Matched Controls and Statistical Significance.

Comparisons between Beetle and pretrained models, such as BLOOM-7b1, are not fully controlled for differences in parameter count, training data, tokeniser, or compute budget; a fuller control would involve training a similarly sized model (e.g., 1B parameters) on a matched FineWeb-based bilingual dataset with uniform sampling, and main results are reported using a single random seed per configuration. In particular, Beetle models use task-specific BPE tokenisers, whereas baselines such as BLOOM and XGLM use different tokenisation schemes, and we aggregate surprisal to the word level by summing subword contributions, which introduces a known source of noise when comparing across tokenisers (Pimentel and Meister, 2024). Within-Beetle comparisons are unaffected, since all compared models within a curriculum share the same tokeniser.

Scope of bilingual acquisition modelling. Our curricula attempt to provide computational analogues of several bilingual acquisition scenarios by manipulating the quantity, timing, and distribution of L1 and L2 exposure. B1 approximates relatively balanced bilingual development, with L1 and L2 available in a stable 50:50 mixture throughout training; B2–B4 approximate different forms of L2 learning, varying the onset, eventual proportion, and temporal distribution of L2 exposure; and B5 approximates late L2 learning following prolonged L1 exposure, providing a setting in which L1 attrition may occur. However, these curricula are not holistic models of bilingual acquisition: human bilingual development is shaped by factors beyond exposure history, including interaction, communicative goals, pragmatics, feedback, social context, and active language use, none of which are represented in our training setup. The curricula should therefore be understood as controlled computational analogues that isolate the role of exposure quantity and curriculum structure, rather than as comprehensive models of balanced bilingualism, L2 learning, or language attri-

tion (Barbenel et al., 2026).

Broader Neurolinguistic and Psycholinguistic Alignment.

The current evaluation focuses on behavioural proxies such as reading-time measures and CEFR-style tasks. We do not yet evaluate alignment with neural signals such as N400 or P600 responses. Extending the analysis to neurophysiological data is left for future work.

9 Reproducibility Statement

All results are produced using a fully versioned and reproducible analysis pipeline. The MECO L2 evaluation follows the mixed-effects specification in Equation 2 (with the baseline model of Equation 1), implemented in the released analysis scripts. Models are trained on multi-node GPU infrastructure (8× A100 80GB). All checkpoints, tokenisers, and evaluation scripts are publicly released, along with the exact CSV files used to generate figures and tables.

10 Ethics Statement

Beetle releases 285 pretrained bilingual and 45 monolingual L2-English language models, tokenisers, and approximately 30 checkpoints per model. **Dataset provenance:** BabyBabelLM and FineWeb-2 are publicly released, license-compatible multilingual web corpora; we do not introduce new web crawls. We release decontaminated and pretokenized datasets for each L1-English pair across scales. The MECO L2 eye-tracking corpus is used under its public licence with anonymous subject IDs only. **Intended use:** Beetle models are scientific instruments for studying bilingual language acquisition and L2 reading dynamics. They are not deployed L2 tutors, and the CEFR-graded evaluation pipeline is for research-grade scoring rather than placement decisions. **Dual-use considerations:** the CEFR-graded text generation capability of these models could in principle be repurposed to draft L2-graded content for assessment fraud (e.g., automated CEFR-tuned essay generation). This risk is mitigated by the small parameter count of the released models (125M), which underperforms publicly-available frontier LLMs on open-ended generation; and we recommend that any downstream pedagogical-tool deployment include detection-of-machine-generated-text safeguards. **Demographic representativeness:** the

released-model L1 sweep covers typologically diverse L1s, but has limited coverage of lower-resourced L1s.

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Appendix

We first describe the Beetle training libraries for bilingual model training (§ [Appendix A](#)) and learning dynamics analysis. The Beetle training and analysis libraries provide a modular framework for controlled hypothesis-driven language modelling. In this paper, we use the Beetle training libraries for training controlled families bilingual language models.

A The Beetle Training Libraries

The Beetle libraries are open-sourced on <https://github.com/beetlelm> to facilitate reproducible controlled language modelling. The main aim of the Beetle libraries is to allow researchers to have modular fine-grained control over all stages of model development, from tokenization to data mixtures. Beetle gives users unusually fine-grained control over pretraining through a single YAML configuration. Rather than treating pretraining as a fixed combination of model, data, and optimisation settings, users can specify the entire training process: the

architecture, representation scheme, data sources, curriculum, optimisation, checkpointing, and measurements collected throughout training.

A.1 beetlelm: The Beetle Training Library

A.1.1 beetle-data

beetle-data is a module that prepares pre-tokenized data for language model training, streaming data from default, or user-specified, training datasets. After data decontamination, beetle-data pretokenises decontaminated data to user-specified training budgets and tokenization. beetle-data first trains tokenizers then producing producing Arrow or Parquet Shards ready for model training. Users define their desired dataset setup in a YAML configuration, specifying the data source (e.g., FineWeb-2 ([Penedo et al., 2025](#))), tokenizer, sequence length, target token budget, and languages to process. Users can organise languages into groups (e.g., core, extension, and low-resource languages) so making it possible to control which languages are processed first and which are run as separate or lower-priority experiments. This is important when preparing datasets for large experimental sweeps, where certain languages might not have enough tokens from a certain training dataset.

Benchmark Decontamination. Benchmark Decontamination during data preprocessing is an important methodological step to avoid over-inflating evaluation performance ([Chai et al., 2026](#)). When streaming raw documents, beetle-data applies a 13-gram benchmark-overlap decontaminator ([Brown et al., 2020b](#)). Reported experiments perform 13-gram decontamination for 19 evaluation metrics: BLiMP ([Warstadt et al., 2020](#)), MultiBLiMP ([Jumelet et al., 2025b](#)), BLiMP-NL ([Suijkerbuijk et al., 2025b](#)), ZhoBLiMP ([Liu et al., 2025b](#)), FLORES-200 ([Goyal et al., 2022](#)), XNLI ([Conneau et al., 2018](#)), UD Treebanks ([De Marneffe et al., 2021](#)), MECO-L2 stimuli ([Siegelman et al., 2025](#)).

A.1.2 Modular Language Model Training

Tokenization Users can choose BPE, Unigram, SuperBPE, or fully byte-level tokenization, to train a tokenizer from specified data, control vocabulary allocation across languages, or supply an existing pretrained tokenizer. This makes tokenization itself an experimental variable rather than an implementation detail.

beetlelm defines tokenization logic in the library’s bilingual module. Modular tokenization logic is implemented in MultilingualTokenizerManager. By default, beetlelm supports three tokenizer types: BPE (Sennrich et al., 2016), Unigram (Kudo, 2018), and SuperBPE (Liu et al., 2025a), implemented using the HuggingFace tokenizers library. Although we only train bilingual tokenizers in this paper, beetlelm is designed to support multilingual tokenization for an arbitrary number of languages. Each language can be assigned an explicit control token (e.g., <lang:en>), while vocabulary size is scaled according to the number of languages. During tokenizer training, an controllable equal-compression sampling procedure, which we use by default in model training, adjusts the amount of data sampled from each language so that each contributes approximately the same number of training tokens. Users can specify tokenizer vocabulary size and compression using YAML. The shared bilingual vocabulary used in the main runs has size 50,304; per-language and shared-trilingual tokenisers are configured separately.

Model Architecture Beetle uses custom PICO decoder stack (Diehl Martinez et al., 2025) by default. The PicoDecoder is a LLaMA-style (Touvron et al., 2023) decoder with $L = 14$ blocks, RMSNorm (Zhang and Sennrich, 2019), grouped-query attention (Ainslie et al., 2023) (12 query heads, 1 key/value head), rotary position embeddings (Su et al., 2024), and SwiGLU feed-forward (Shazeer, 2020) expanding to $4d$ and projecting back to d . Sequence length is 512 under BF16-mixed precision. Width is the only scale-dependent hyper-parameter: $d \in \{96, 384, 768, 1536\}$ for the tiny, small, medium, and large variants. The 125M-parameter “medium” variant ($d = 768$, 12 heads, 1 KV head, 14 layers) is used for every reported run.

Alternative Architectures beetlelm implements different architectures to enable controlled comparisons between different bilingual models: **BGPT**, a GPT-2-style decoder with learned positional embeddings used in Arnett et al. (2025). Additionally, the library implements **BeetleMoE**, a top- k mixture-of-experts model with ST-MoE auxiliary routing losses; and **BeetleSSM**, which replaces attention blocks with Mamba-style state-space modules.

Curriculum Parameterisation in Beetle

Curricula are defined in beetlelm using DataMixConfig which defines bilingual curricula BALANCED (B1) and SEQUENTIAL (B3), together with additional sampling mechanisms. Users can modify this to add new custom curricula for multilingual language modelling or computational cognitive modelling (e.g., to model language attrition or heritage learning scenarios). Custom data mixtures (exposure curricula) can be defined using YAML configurations to specify multiple language or dataset sources, L1 and L2 streams, and data-mixing strategies including balanced, sequential, late, part-time, and named curricula.

The beetlelm library abstracts data mixtures as continuous exposure schedules rather than as discrete training phases with fixed boundaries. Formally, each curriculum defines a time-varying language mixture $w(t) \in \Delta^{|L|}$ over normalised training progress $t \in [0, 1]$, where $\Delta^{|L|}$ denotes the simplex over the set of languages L . Progress t may be measured either in optimisation steps or in tokens seen. At every point during training, $w_l(t)$ specifies the probability mass assigned to language l , with $\sum_l w_l(t) = 1$. All curriculum conditions are constructed compositionally from four schedule primitives, summarised in Table 2. This abstraction allows users to compose YAML specifying when new training data can be introduced at certain training steps in specified ratios from different data sources.

A bilingual curriculum is a time-dependent mixture $\mathcal{D}_{\text{mix}}(t) = \alpha(t) \mathcal{D}_1 \cup (1 - \alpha(t)) \mathcal{D}_2$, where $\alpha(t) \in [0, 1]$ is the per-step L2 sampling probability and $t \in [0, T]$ indexes training. The polyglot generalisation is a language-exposure vector $\alpha(t) = (\alpha_1(t), \dots, \alpha_N(t))$ with $\sum_i \alpha_i(t) = 1$. Each schedule maps a normalised progress value $p \in [0, 1]$ to a per-language sampling weight; phase boundaries are discrete events that trigger EWC snapshots in continual-learning runs. Rather than specifying $\alpha(t)$ as an arbitrary continuous function, we represent curricula as a sequence of discrete phases $\mathcal{C} = \{(\tau_k^{\text{start}}, \tau_k^{\text{end}}, \mathbf{w}_k)\}_{k=1}^K$, where $\mathbf{w}_k \in \mathbb{R}^N$ satisfies $\sum_i w_{k,i} = 1$; for $\tau_k^{\text{start}} \leq t/T < \tau_k^{\text{end}}$ we set $\alpha(t) = \mathbf{w}_k$. This declarative phase representation is used in every reported run. This is implemented in the bilingual module of beetlelm.

	B1	B2	B3	B4	B5
<i>Design</i>					
L2 onset	0	50%	50%	0	80%
Target L2	50%	50%	67%	20%	50%
Transition	none	sig.	sig.	bursts	sig.
Episodic	no	no	no	yes	no
CL overlay	none	none	none	none	none
<i>Realised (corrected sampler)</i>					
L2 onset	0	33%	32%	17%	62%
L2-only phase	none	47–76%	45–100%	none	75–100%
L2, last 10%	50%	50%	100%	20%	100%
L2, whole run	50%	50%	62%	17%	33%
L2 range	50%	2–100%	2–100%	9–35%	2–100%

Table 2: Implementation of the five curricula, B1 – B5 in the beetlelm library.

Checkpointing beetlelm checkpointing can be configured at arbitrary steps or according to a phase-aware logarithmic schedule, with options for automatic resumption, local checkpoint retention. Following Pico (Diehl Martinez et al., 2025), model states are saved in both PyTorch and Hugging Face-compatible formats (Wolf et al., 2019), enabling straightforward loading with vanilla PyTorch or integration into the Hugging Face ecosystem for fine-tuning, inference, and model sharing. At user-defined intervals, the library also records layerwise intermediate activations and gradients from the current training batch, with the option to use a fixed evaluation batch for consistent comparisons across training. The corresponding training batch is saved alongside these tensors, providing a complete record of the data underlying each measurement. Users can additionally define evaluation metrics, such as validation perplexity or accuracy, which are stored alongside each checkpoint. All checkpoints are automatically uploaded to and version-controlled on Hugging Face, allowing researchers to revisit any point in training and analyse how the model’s representations, gradient flows, and performance evolved over time.

Continual Learning The BeetleLM library contains **fifteen** modular continual-learning strategies, which are grouped in five families, summarised in Table 3.

Parameter regularisation: Parameter-regularisation methods reduce forgetting by penalising changes to parameters that are important for previously learned phases. beetlelm implements *Elastic Weight Consolidation* (EWC) (Kirkpatrick et al., 2017) with regularisation strength $\lambda_{\text{EWC}} \in 0, 1, 5, 10, 20, 40$; at each phase

boundary, parameter importance is estimated from the diagonal of the Fisher information matrix and used to penalise subsequent parameter changes. beetlelm additionally implements *Synaptic Intelligence* (SI) (Zenke et al., 2017) and *Memory Aware Synapses* (MAS) (Aljundi et al., 2018), which estimate parameter importance from the contribution of individual parameters to loss reduction and from the sensitivity of the model output to parameter changes, respectively. These methods form the standard importance-based regularisation family in continual learning (Benzing, 2022).

Generative and similarity replay: Replay methods mitigate forgetting by reintroducing information from earlier phases, either by storing representative examples or by generating pseudo-examples (Lopez-Paz and Ranzato, 2017; Robins, 1995; Sun et al., 2020). beetlelm implements *Language MOdeling for Lifelong Language Learning* (LAMOL) (Sun et al., 2020) with replay-loss weight $\lambda_{\text{replay}} \in 0, 0.1, 0.25, 0.5$, *Instruction-based Continual Learning* (InsCL)-style similarity replay (Wang et al., 2024b) using cosine-similarity and Wasserstein-distance centroids, and episodic-sample replay buffers following experience-replay approaches to continual learning (Lopez-Paz and Ranzato, 2017).

Meta-learning: Meta-learning methods optimise models to adapt efficiently to new tasks or phases while retaining parameters that support generalisation across tasks (Finn et al., 2017; Nichol et al., 2018). beetlelm implements *first-order Model-Agnostic Meta-Learning* (FO-MAML) (Finn et al., 2017) and *Self-Meta-Learning for Language Models* (SMLMT) (Bansal et al., 2020; Diehl Martinez et al., 2025), varying the hybrid-training ratio $r_{\text{meta}} \in 0, 0.1, 0.2, 0.3, 0.4$ and the inner-loop episode configuration over $N \in 2, 4, 8$ ways and $k \in 1, 5$ shots.

Distillation: Knowledge-distillation methods preserve previously acquired behaviour by encouraging a model trained on a new phase to match the predictions or internal representations of an earlier model (Hinton et al., 2015; Li et al., 2018). beetlelm implements output-level *knowledge distillation* (KD) (Hinton et al., 2015).

Architectural and auxiliary-loss methods: Architectural and auxiliary-loss approaches modify the model structure, optimisation dynamics, or training objective to alter the stability–plasticity

trade-off or provide useful inductive biases before or during subsequent learning (Li et al., 2018). beetlelm implements *Transfer, Incremental Learning and Transfer* (TILT) which is used in Papadimitriou and Jurafsky (2020); an exposure-dependent learning-rate plasticity boost, ALiBi-scheduler decay based on *Attention with Linear Biases* (ALiBi) (Press et al., 2022), and Shuffle-Dyck pre-pretraining, motivated by recent work showing that pre-pretraining on formal languages can provide useful structural biases for subsequent language-model training (Hu et al., 2025; Yamaguchi et al., 2026; Guo et al., 2026).

Model Training Users control the total number of optimisation steps, sequence length, batch size, accelerator configuration, distributed-training strategy, numerical precision, optimiser, learning rate, weight decay, scheduler, and warm-up. Curriculum mixing can additionally be controlled independently through its own configuration.

Training hyperparameters for reported experiments are in Table 4. Training was conducted on 8× A100s (64GB). 100M and 2B tokens 125M models can be trained in under an hour on 1 A100. 24B token models take around 5 hours on 8× A100s.

B Bilingual and Second Language Evaluation Methodology

beetle-analyze is a library for evaluating bilingual language models and their learning dynamics. In this paper, we specifically focus on evaluation of different aspects of second-language competence. MECO measures graded processing alignment through reading-time prediction. BLISS (Gao et al., 2025) tests categorical grammatical knowledge, and its triplet design—contrasting a corrected form, a genuine learner error, and a synthetic error, which additionally asks whether a model internalises an L2-specific interlanguage error structure rather than a generic notion of ungrammaticality. JFLEG (Napoles et al., 2017) tests whether a model prefers corrected forms over learner productions, connecting the framework to grammatical error correction.

We aim to include additional evaluations to facilitate modelling and evaluation of computational models of bilingual and multilingual learning. Because Beetle employs a shared vocabulary under controlled exposure schedules, it offers a plat-

form for studying bilingual-specific phenomena that lie beyond monolingual processing. Candidate directions include lexical facilitation and cognate effects of the kind modelled by Dijkstra and Van Heuven (2002), the resolution of interlingual homographs, code-switching and the switch costs documented in the bilingual production and comprehension literature (Meuter and Allport, 1999; Gollan and Ferreira, 2009), and cross-linguistic syntactic interference (Hartsuiker et al., 2004). These phenomena are noted here as future directions that the controlled-exposure design of the framework is well placed to support.

C Details of Beetle MECO Analyses

For each target word w_i , we compute autoregressive surprisal $S(w_i) = -\log P(w_i \mid w_{<i})$ on the relevant Beetle and baseline models. Following previous work, (e.g., Wilcox et al., 2023), we fit mixed-effects regressions predicting first-pass reading time from current-word and spillover surprisal while controlling for word length, frequency, and sentence position, and evaluate language model alignment with reading time based on the fit of the regressions to the data.

We fit a linear mixed-effects regression models to MECO first-pass duration (also known as *gaze duration*) data from MECO waves 1 + 2 based on our predictors. We first fit baseline regressions with each word’s position in the sentence, length in characters, and frequency as main effects, as well as each the preceding two words’ length and frequency; and include by-subject uncorrelated random slopes for each of these as well as random intercepts for each subject:

$$\begin{aligned} \text{first_pass} \sim & \text{position}(w_i) + \text{len}(w_i) \\ & + \text{len}(w_{i-1}) + \text{len}(w_{i-2}) \\ & + \text{freq}(w_i) + \text{freq}(w_{i-1}) \\ & + \text{freq}(w_{i-2}) \\ & + (1 + \text{position}(w_i) + \text{len}(w_i) \\ & \quad + \text{len}(w_{i-1}) + \text{len}(w_{i-2}) \\ & \quad + \text{freq}(w_i) + \text{freq}(w_{i-1}) \\ & \quad + \text{freq}(w_{i-2}) \parallel \text{subject}) \end{aligned} \quad (1)$$

We then fit linear mixed-effects regressions that included all the baseline predictors in addition to the surprisal of the current and previous two words, which were also included as uncorrelated random slopes:

Family	Strategy	Mechanism	Key hyperparameters
<i>Parameter regularisation</i>			
	EWC (Kirkpatrick et al., 2017)	Diagonal-Fisher quadratic penalty at phase change	$\lambda \in [0, 40]$, $K_{\text{Fisher}} = 10$
	SI	Online importance accumulation	c , damping
	MAS	Gradient-magnitude importance	λ
<i>Replay</i>			
	LAMOL (Sun et al., 2019)	Pseudo-sample generation, nucleus sampling	$\lambda_{\text{replay}} \in [0, 0.5]$, top- p
	InsCL similarity replay	Centroid-similarity weighted replay	cosine/Wasserstein, buffer size
	Episodic replay	Stored exemplars, uniform sampling	buffer size, mix ratio
<i>Meta-learning</i>			
	MAML / SMLMT	Inner-loop adaptation on (S, Q) splits	hybrid ratio $\in [0, 0.4]$, N -way, k -shot
<i>Distillation</i>			
	Hinton-KD	Soft-target cross-entropy against pre-L2 anchor	T , λ_{KD}
	Self-distillation	Same model as teacher at earlier checkpoint	checkpoint offset
	FitNets feature distill.	Hidden-state ℓ_2 alignment	layer-pair list
<i>Architectural / auxiliary loss</i>			
	TILT freeze-and-extend	Freeze backbone; train embeddings + LM head	frozen modules
	Exposure-LR plasticity	Token-exposure LR with phase-transition boost	boost $\in [1, 3]$, warmup tokens
	ALiBi scheduler	Time-varying ALiBi slopes across phases	initial/final slope, decay shape
	Shuffle-Dyck pre-pretraining	Formal-language warmup before NL	steps, depth
	EWC + MAML stack	Composite of regularisation + meta-learning	paired hyperparameters

Table 3: The continual-learning strategies implemented in the Beetle training library. The experiments reported here use EWC, LAMOL, and exposure-LR plasticity overlays.

$$\begin{aligned}
\text{first_pass} \sim & \text{Surprisal}(w_i) \\
& + \text{Surprisal}(w_{i-1}) \\
& + \text{Surprisal}(w_{i-w}) \\
& + (1 + \text{Surprisal}(w_i) \\
& \quad + \text{Surprisal}(w_{i-1}) \\
& \quad + \text{Surprisal}(w_{i-w}) \parallel \text{subject}) \\
& + \text{baseline_predictors}
\end{aligned} \tag{2}$$

Since we hold all regression predictors constant except the surprisal terms, we consider language models with surprisal terms that lead to better fits (i.e., higher log-likelihoods) to first-pass duration to be models that better align with reading time. For easier comparison, we subtract the log-likelihood of the baseline regressions to get $\Delta \log L$:

$$\Delta \log L = \log L(\text{full}) - \log L(\text{baseline}). \tag{3}$$

We thus compare language model alignment with reading time based on the $\Delta \log L$ of regressions that include surprisal calculated using them.

The script used to fit the regressions is released with the code. Sample sizes are on the order of tens of subjects and tens of thousands of word-level observations.

D BLiSS and Pedagogical Evaluation

We evaluate whether curriculum effects observed in reading-time prediction extend to grammatical discrimination and pedagogical benchmarks. First, we consider BLiSS (Gao et al., 2025), which evaluates preference behaviour over L2 error triplets, consisting of a corrected sentence s_{corr} , a human learner error s_{lrn} , and an artificial error s_{art} . We compute token-normalized surprisal:

$$\text{BPT}(s) = -\frac{1}{|s|} \sum_{t=1}^{|s|} \log_2 p(w_t \mid w_{<t}),$$

where lower values indicate higher model plausibility.

We report four metrics following Gao et al. (2025). **Learner Preference (LP)** measures whether s_{lrn} is preferred over s_{corr} ($\text{BPT}(s_{\text{lrn}}) < \text{BPT}(s_{\text{corr}})$). This metric is informative but does not distinguish between grammatical competence and learner simulation behavior. **Human vs. Artificial Preference (HAP)** measures whether s_{lrn} is preferred over s_{art} , and **HAP- τ** applies a margin constraint for robustness. **Strict Order (SO)** requires the full ordering $s_{\text{corr}} \prec s_{\text{lrn}} \prec s_{\text{art}}$. We report all metrics separately as they capture different aspects of model behavior.

Hyperparameter	100M	2B	24B
Architecture	PicoDecoder	PicoDecoder	PicoDecoder
Parameters	125M	125M	125M
Layers	14	14	14
d_{model}	768	768	768
Heads (Q/KV)	12 / 1	12 / 1	12 / 1
FFN size	3072	3072	3072
Sequence length	512	512	512
Vocabulary	50K	50K	50K
Languages	9	20	20
Dataset	BabyBabel FineWeb-2	FineWeb-2	FineWeb-2
Optimizer	AdamW	AdamW	AdamW
Learning rate	5×10^{-4}	5×10^{-4}	5×10^{-4}
Weight decay	0.01	0.01	0.01
Warmup steps	500	381	625
Micro-batch	64	64	64
Effective batch	64	512	512
Tokens / step	32768	262144	262144
Max steps	10000	7629	91552
Precision	bf16	bf16	bf16
Strategy	DDP	DDP	DDP
Devices	8×A100	8×A100	8–64×A100

Table 4: Training hyperparameters across data scales.

D.1 Detailed Beetle BLiSS Results

Table 5 and Table 6 show BLiSS accuracy of Beetle and LLMs. The overall performance is summarised in Figure 6. Beyond this headline accuracy, the detailed BLiSS table (Table 6) decomposes performance into RP@0 and RP@ τ (random-over-human preference, with and without a margin), NGS (normalised gap score), and CPS (correct-preferred sanity check); reporting these additional metrics separates whether models merely prefer human over random productions (RP@0) from whether they do so by a robust margin (RP@ τ), and confirms the effect is not a scoring artefact (CPS/NGS), giving a finer-grained picture than the headline accuracy in Figure 6. We briefly summarise the main results.

Curriculum effects on BLiSS On BLiSS, staged curricula (B2, B3-33, B5) outperform B1, but effect sizes are smaller than those observed on MECO (Fig. 5). On FineWeb nld-eng, the ordering is B3-33 > B5 > B2 > B4 > B1, compared to a larger separation in MECO (approximately $78 \Delta \log L$). The best-performing curriculum varies by L1: B3-33 ranks highest for Germanic L1s, while B5 ranks highest for Chinese L1. Within Beetle, BLiSS and MECO induce different curriculum rankings (Spearman $\rho = -0.47$,

			BLiSS (matched-L1 cohort)			
Model	Params	L1	RP@0	RP@ τ	NGS	CPS
BLOOM-560M	0.56B	Dutch	59.0	52.7	55.4	55.8
		German	58.9	50.7	54.9	52.3
		Chinese	70.2	62.1	65.0	56.1
BLOOM-1.1B	1.1B	Dutch	59.7	51.6	55.8	56.6
		German	57.6	49.4	54.7	53.1
		Chinese	70.3	63.6	65.7	56.6
BLOOM-1.7B	1.7B	Dutch	59.0	51.3	55.9	56.6
		German	57.3	50.2	54.7	55.7
		Chinese	70.5	63.7	65.7	58.4
BLOOM-7.1B	7.1B	Dutch	63.1	57.2	58.3	58.8
		German	59.3	50.0	55.7	56.7
		Chinese	73.2	65.6	67.4	57.5
XGLM-4.5B	4.5B	Dutch	62.0	54.0	57.5	63.2
		German	59.3	50.6	55.3	58.1
		Chinese	73.7	65.7	67.3	59.8
EuroLLM-9B	9B	Dutch	64.4	56.3	57.5	61.6
		German	60.3	50.8	55.1	61.3
		Chinese	73.7	65.4	67.5	61.1
Gemma-3-270M	0.27B	Dutch	60.8	55.1	57.2	56.9
		German	57.2	51.9	55.3	53.6
		Chinese	72.0	66.5	66.7	56.1
Gemma-2-2B	2B	Dutch	64.7	57.4	58.1	56.1
		German	63.0	56.8	58.5	55.2
		Chinese	75.9	71.3	69.6	54.5
Gemma-2-9B	9B	Dutch	65.5	60.4	59.7	54.5
		German	66.0	60.4	60.0	55.4
		Chinese	75.3	71.4	70.4	55.2
Gemma-2-27B	27B	Dutch	69.0	61.3	63.0	55.7
		German	68.1	59.3	62.0	52.1
		Chinese	75.2	70.0	70.3	54.2
Qwen3-0.6B	0.6B	Dutch	59.5	54.1	55.7	60.3
		German	57.8	49.9	55.4	57.4
		Chinese	70.9	62.2	65.4	60.9
Qwen3-4B	4B	Dutch	63.2	55.7	58.9	61.2
		German	60.3	53.4	55.7	59.4
		Chinese	72.8	66.1	67.3	56.3
Qwen3-8B	8B	Dutch	65.4	57.0	59.5	62.0
		German	59.9	52.6	56.3	57.6
		Chinese	75.2	67.7	68.9	57.7
Llama-3.2-1B	1B	Dutch	63.5	54.9	57.9	60.8
		German	61.2	53.5	56.5	59.2
		Chinese	73.9	66.1	67.7	60.1
Llama-3.1-8B	8B	Dutch	67.0	58.7	60.7	60.6
		German	62.4	54.8	58.0	57.3
		Chinese	75.8	68.7	69.2	59.3

Table 5: BLiSS learner-minimal-pair scores (% , 0–100) for frontier multilingual-LLM baselines, scored per L1 cohort. *Params* gives the parameter count and *L1* the cohort. Cell shading encodes score on a fixed scale (darker green = higher). Per model, the highest value in each metric column is in **bold**. Metrics: RP@0 / RP@ τ (random-over-human preference, with and without a margin), NGS (normalised gap score), CPS (correct-preferred sanity check).

$p < 0.001$).

Summary across discrimination tasks Across BLiSS, curriculum differences are smaller than those observed for MECO reading-time prediction (subsection D.1). Best-performing curricula vary by L1 (B3-33 for Germanic, B5 for Chinese), with no single schedule dominating across settings. In contrast, staged curricula only dom-

BLISS (matched-L1 cohort)						
Pair	Data	Curr.	RP@0	RP@ τ	NGS	CPS
tur-eng	100M tok B1		57.5	50.2	55.7	50.6
	100M tok B4		56.3	48.3	55.6	43.0
	100M tok B5		56.1	49.1	55.4	48.7
	100M tok Mono		53.5	45.0	52.4	34.1
	2B tok B1		55.9	49.7	54.7	54.1
	2B tok B2		57.2	50.4	54.8	54.4
	2B tok B3		56.3	50.0	54.5	54.1
	2B tok B4		57.6	52.2	56.3	52.2
	2B tok B5		58.0	51.7	55.8	52.9
	2B tok Mono		56.6	48.9	55.8	41.3
arb-eng	100M tok Mono		48.4	33.8	48.3	30.1
hin-eng	100M tok B1		54.8	44.3	54.3	53.8
	100M tok B4		54.3	41.5	53.9	46.7
	100M tok B5		54.5	43.7	53.7	53.0
	100M tok Mono		51.1	38.2	51.0	35.2
	2B tok B1		56.0	45.6	53.1	60.9
	2B tok B2		53.7	45.0	52.7	58.5
	2B tok B3		54.9	43.2	52.8	60.4
	2B tok B4		55.7	45.1	54.7	57.8
	2B tok B5		55.3	46.4	54.0	58.3
	2B tok Mono		57.1	45.6	56.3	43.5
ita-eng	100M tok B1		62.6	51.3	59.7	49.3
	100M tok B4		62.6	50.3	60.7	43.5
	100M tok B5		61.5	50.6	59.6	47.5
	100M tok Mono		58.8	46.7	58.3	35.1
	2B tok B1		60.3	51.1	57.7	54.1
	2B tok B2		61.2	51.0	57.6	54.2
	2B tok B3		60.2	50.8	57.4	54.3
	2B tok B4		62.3	52.2	59.3	52.7
	2B tok B5		61.6	52.0	58.5	54.5
	2B tok Mono		62.9	51.2	60.9	39.4

BLISS (matched-L1 cohort)						
Pair	Data	Curr.	RP@0	RP@ τ	NGS	CPS
nld-eng	Human-scale B1		56.6	48.9	55.2	48.4
	Human-scale Mono		55.3	44.6	54.6	32.3
	100M tok B1		57.1	50.1	57.2	48.9
	100M tok B5		57.1	49.0	56.9	48.8
	100M tok Mono		59.0	48.5	57.5	35.4
	2B tok B1		56.6	48.6	54.9	56.8
	2B tok Mono		60.7	54.0	58.9	44.0
	24B tok B1		54.8	48.5	54.7	54.3
	24B tok B2		55.7	50.3	53.9	56.1
	24B tok B3		55.3	48.5	53.8	56.5
	24B tok B4		58.5	51.3	56.1	55.2
	24B tok B5		56.8	48.8	54.1	57.0
	24B tok Mono		59.0	50.5	57.3	46.3
deu-eng	Human-scale B1		57.2	48.2	55.5	46.8
	Human-scale Mono		51.0	38.3	51.3	29.5
	100M tok B1		54.6	45.8	54.4	50.1
	100M tok B4		54.9	45.5	55.7	44.0
	100M tok B5		56.1	47.1	55.3	48.1
	100M tok Mono		56.6	46.6	56.5	35.4
	2B tok B1		53.1	46.8	53.0	52.0
	2B tok B3		56.2	46.3	55.9	40.3
	2B tok Mono		57.8	46.9	57.1	40.0
	24B tok B1		54.2	45.7	52.7	53.3
	24B tok B2		54.8	47.4	53.7	50.3
	24B tok B3		55.1	47.4	53.5	53.0
	24B tok B4		54.7	47.3	53.9	51.7
	24B tok B5		54.3	46.8	52.8	52.8
	24B tok Mono		55.5	45.4	55.6	42.4

BLISS (matched-L1 cohort)						
Pair	Data	Curr.	RP@0	RP@ τ	NGS	CPS
jpn-eng	100M tok B1		62.2	47.7	59.9	47.2
	100M tok B2		62.6	48.4	60.1	48.8
	100M tok B3		62.3	48.8	59.6	49.2
	100M tok B4		60.2	42.5	58.2	40.2
	100M tok B5		62.0	47.5	59.5	48.5
	100M tok Mono		54.3	37.4	52.9	34.1
pol-eng	100M tok B1		55.0	47.1	54.3	54.6
	100M tok B4		53.6	43.9	54.1	49.4
	100M tok B5		52.9	44.8	53.1	52.4
	100M tok Mono		51.8	42.6	51.7	40.3
	2B tok B1		55.4	48.4	54.0	59.5
	2B tok B2		55.0	48.1	53.5	58.8
spa-eng	100M tok B1		61.3	49.2	59.0	48.0
	100M tok B2		61.3	50.0	58.9	48.4
	100M tok B3		60.9	49.8	58.3	50.9
	100M tok B4		60.4	49.1	59.0	43.8
	100M tok B5		60.9	58.0	59.1	48.8
	100M tok Mono		55.0	43.4	54.7	31.8
	2B tok B1		59.4	49.6	56.8	54.0
	2B tok B2		60.1	49.5	57.0	54.3
	2B tok B3		59.6	49.6	56.9	55.1
	2B tok B4		59.8	50.0	57.9	51.8
	2B tok B5		58.9	49.1	56.7	54.5
	2B tok Mono		58.8	46.8	57.8	36.8

BLISS (matched-L1 cohort)						
Pair	Data	Curr.	RP@0	RP@ τ	NGS	CPS
zho-eng	Human-scale B1		68.7	58.9	65.0	49.1
	Human-scale Mono		45.4	22.0	46.5	25.5
	100M tok B1		69.3	58.7	65.1	48.1
	100M tok B2		69.2	60.1	65.3	47.5
	100M tok B3		69.0	60.7	65.0	48.9
	100M tok B4		66.2	53.9	63.0	42.9
	100M tok B5		67.7	58.8	64.3	46.8
	100M tok Mono		58.2	47.0	56.5	29.1
	2B tok B1		69.8	61.7	64.8	54.8
	2B tok B2		70.2	62.4	64.8	54.6
	2B tok B3		68.3	61.2	63.6	55.2
	2B tok B4		69.0	62.1	64.7	51.9
	2B tok B5		70.7	63.3	65.0	53.8
	2B tok Mono		65.9	56.2	63.5	33.2
eng-nld	2B tok B1		69.5	62.0	64.5	55.7
	24B tok B2		69.4	61.2	64.3	55.3
	24B tok B3		68.8	61.1	63.4	55.4
	24B tok B4		70.0	62.3	65.3	53.3
eng-deu	24B tok B5		68.8	61.1	64.1	57.9
	24B tok Mono		64.7	55.0	62.9	36.6
eng-nld	2B tok B1		56.8	50.2	54.7	54.7
eng-deu	2B tok B1		54.6	46.3	52.9	51.8

Table 6: BLISS matched-L1 Scores for Beetle models across L1s (Turkish, Arabic, Hindi, Italian, Japanese, Polish, Spanish). These L1s are represented in second language learner corpora (Gao et al., 2025).

inate on MECO reading-time alignment, indicating a clear separation between fluency/correction-based judgments and online processing measures.

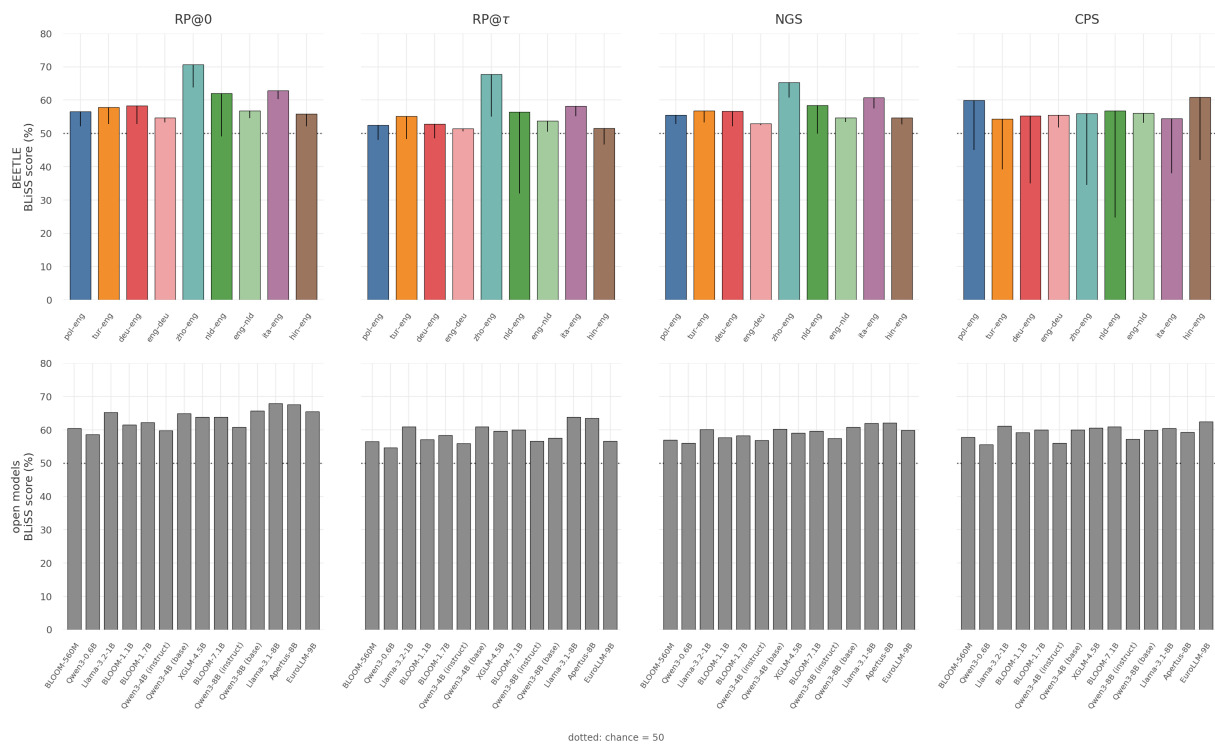


Figure 6: Overall BLiSS learner-minimal-pair accuracy for Beetle models against baseline-matched multilingual LLMs, aggregated across the matched-L1 cohorts. Curriculum differences on BLiSS are smaller than the corresponding differences in MECO reading-time alignment.

D.2 CEFR Task Performance

This section reports Beetle’s performance on the CEFR-aligned and other pedagogical evaluations. Across pedagogical evaluations (Figure 7), balanced exposure (B1) consistently performs best on cloze and CEFR-style metrics.

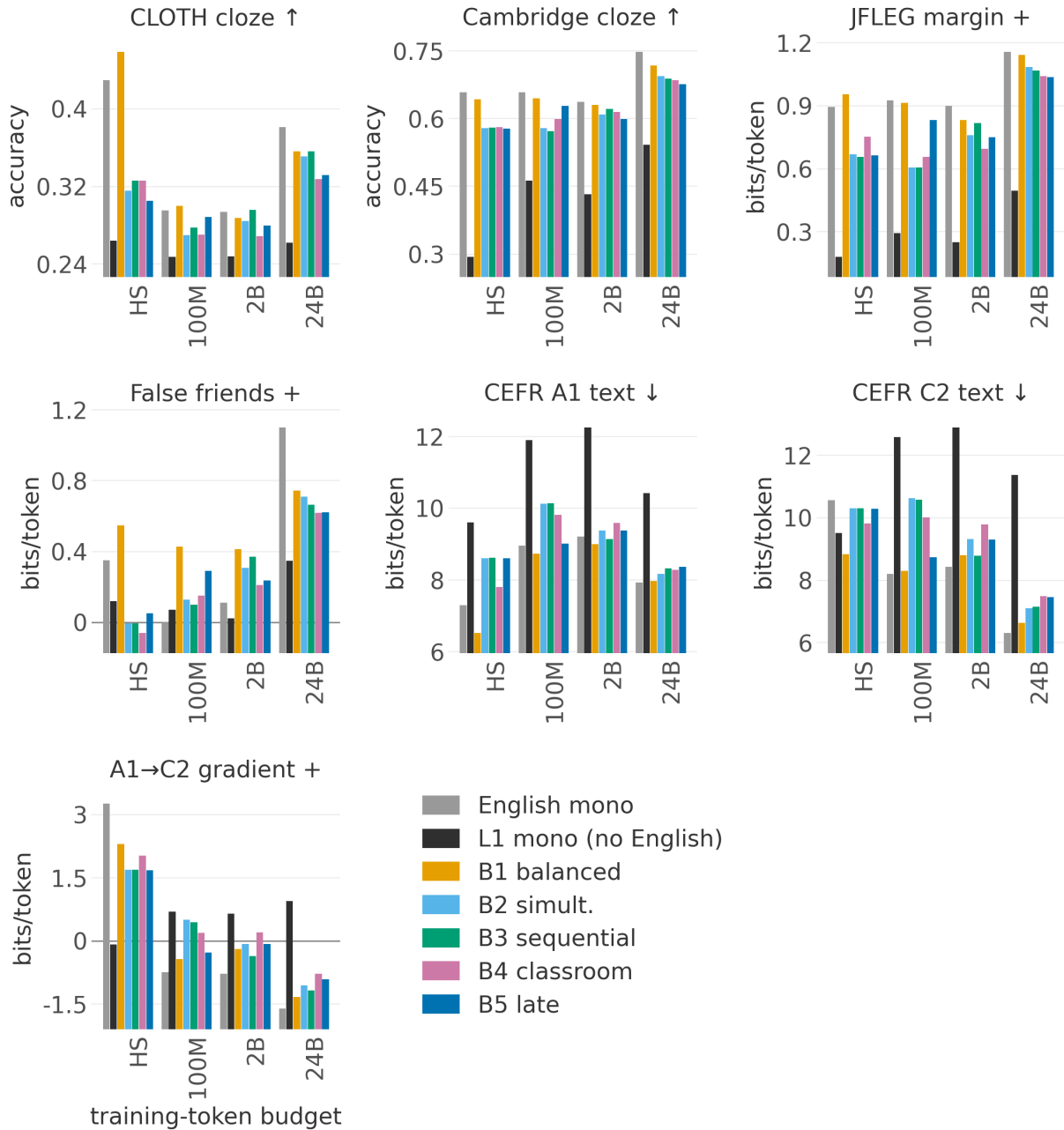


Figure 7: Performance of Beetle 125M models across pedagogical evaluations (CLOTH and Cambridge cloze, JFLEG grammatical correction, false-friend disambiguation, and the CEFR perplexity gradient), by curriculum and training scale. Balanced exposure (B1) is consistently strongest on these fluency- and correction-based measures.

Fig. 7 shows performance of Beetle on different pedagogical tasks. The individual benchmarks measure the following:

- **CLOTH** (Xie et al., 2018): a large cloze test of English built from middle/high-school exam passages; closed multiple-choice gap-filling measuring grammatical and lexical competence.
- **Cambridge cloze**: open-cloze items from Cambridge English exams graded by CEFR level; the model must supply the missing word, testing productive grammatical knowledge (Mullooly, 2023).

- **JFLEG grammatical correction** (Napoles et al., 2017): a fluency/grammatical-error-correction benchmark; we score the model's preference (bits/token margin) for the corrected sentence over the learner-error version (positive = prefers the correction).
- **False-friend disambiguation**: cognate/false-friend minimal pairs; the margin (bits/token) by which the model prefers the contextually correct sense over the interlingual-homograph distractor.
- **CEFR perplexity gradient** (Arase et al., 2022): the monotonic change in bits-per-token from CEFR-A1 to CEFR-C2 graded texts; a well-calibrated model should assign lower perplexity to easier (A1) than harder (C2) material, so the A1→C2 gradient indexes proficiency sensitivity.

E Detailed Beetle BLiMP and MultiBLiMP results

			MultiBLiMP		MonoBLiMP	
Pair	Data	Curr.	L1	Eng	L1	Eng
eus-eng	100M tok B1		97.4	85.5	-	62.1
	100M tok B4		96.0	75.8	-	56.0
	100M tok B5		93.0	81.3	-	60.7
	100M tok Mono		98.2	69.4	-	52.2
tur-eng	100M tok B1		76.6	84.4	74.6	61.1
	100M tok B4		72.5	73.6	73.1	54.2
	100M tok B5		72.2	81.3	61.5	61.0
	100M tok Mono		76.6	65.3	78.1	52.2
	2B tok B1		87.8	92.2	85.6	69.0
	2B tok B2		83.1	93.4	86.2	69.9
	2B tok B3		69.4	93.6	57.8	69.5
	2B tok B4		87.3	88.8	87.7	65.3
	2B tok B5		77.5	90.4	80.8	66.5
	2B tok Mono		87.3	69.2	87.8	51.7
ell-eng	100M tok B1		90.1	83.6	-	59.7
	100M tok B2		87.8	83.9	-	60.5
	100M tok B3		72.4	86.8	-	61.9
	100M tok B4		92.1	78.3	-	55.4
	100M tok B5		79.7	84.0	-	59.8
	100M tok Mono		90.4	67.5	-	52.8
est-eng	100M tok B1		73.7	84.7	-	59.6
	100M tok B2		70.6	84.5	-	60.5
	100M tok B3		59.1	88.6	-	61.6
	100M tok B4		77.0	77.9	-	56.0
	100M tok B5		65.6	81.4	-	59.9
	100M tok Mono		80.2	68.1	-	51.8
fin-eng	100M tok B1		80.2	83.2	-	59.9
	100M tok B2		77.4	86.2	-	60.5
	100M tok B3		67.5	86.8	-	61.2
	100M tok B4		79.6	72.9	-	53.1
	100M tok B5		71.4	83.0	-	60.1
	100M tok Mono		83.9	69.0	-	50.4
heb-eng	100M tok B1		72.5	83.8	-	60.0
	100M tok B2		69.8	85.2	-	60.0
	100M tok B3		68.2	77.3	-	55.7
	100M tok B4		73.1	77.7	-	56.1
	100M tok B5		66.6	82.3	-	59.3
	100M tok Mono		76.5	65.3	-	53.3
arb-eng	100M tok Mono		82.6	67.7	-	54.0
dan-eng	100M tok B1		96.0	84.3	-	62.7
	100M tok B2		98.0	83.6	-	63.0
	100M tok B3		70.0	86.6	-	64.0
	100M tok B4		100.0	76.4	-	58.9
	100M tok B5		94.0	81.3	-	60.7
	100M tok Mono		98.0	65.3	-	53.6
fil-eng	100M tok B1		-	86.1	-	65.0
	100M tok B4		-	79.7	-	60.8
	100M tok B5		-	85.6	-	63.1
	100M tok Mono		-	69.5	-	57.3
hin-eng	100M tok B1		87.6	86.4	-	63.8
	100M tok B4		87.6	75.8	-	57.3
	100M tok B5		80.6	79.9	-	62.1
	100M tok Mono		87.6	67.7	-	53.1
	2B tok B1		95.8	93.5	-	72.4
	2B tok B2		94.5	93.6	-	72.0
	2B tok B3		69.2	91.9	-	72.4
	2B tok B4		97.0	89.5	-	67.8
	2B tok B5		89.6	91.2	-	68.0
2B tok Mono		97.8	70.4	-	55.7	

			MultiBLiMP		MonoBLiMP	
Pair	Data	Curr.	L1	Eng	L1	Eng
isl-eng	100M tok	B1	88.6	83.0	-	60.2
	100M tok	B2	87.1	85.6	-	60.9
	100M tok	B3	69.8	88.3	-	62.2
	100M tok	B4	88.9	75.7	-	56.5
	100M tok	B5	77.2	84.5	-	62.1
	100M tok	Mono	92.0	67.0	-	51.0
ita-eng	100M tok	B1	81.7	87.8	-	62.7
	100M tok	B4	79.5	73.5	-	56.1
	100M tok	B5	66.8	82.6	-	61.6
	100M tok	Mono	80.9	69.2	-	53.4
	2B tok	B1	91.3	93.0	-	69.8
	2B tok	B2	90.4	93.1	-	70.5
	2B tok	B3	68.4	93.8	-	71.6
	2B tok	B4	92.4	92.3	-	66.9
	2B tok	B5	85.0	91.7	-	68.5
	2B tok	Mono	93.4	69.7	-	54.9
jpn-eng	100M tok	B1	-	79.6	-	61.2
	100M tok	B2	-	81.6	-	63.0
	100M tok	B3	-	85.3	-	63.5
	100M tok	B4	-	71.3	-	57.3
	100M tok	B5	-	80.1	-	60.0
	100M tok	Mono	-	66.0	-	53.7
kor-eng	100M tok	B1	-	83.6	-	61.9
	100M tok	B2	-	86.1	-	63.1
	100M tok	B3	-	87.8	-	63.6
	100M tok	B4	-	71.3	-	57.0
	100M tok	B5	-	82.6	-	61.8
	100M tok	Mono	-	64.4	-	52.1
pol-eng	100M tok	B1	77.8	86.6	-	62.2
	100M tok	B4	76.6	78.4	-	57.1
	100M tok	B5	68.7	83.4	-	60.1
	100M tok	Mono	78.8	65.3	-	53.0
	2B tok	B1	92.4	92.6	-	69.5
	2B tok	B2	90.2	91.3	-	70.1
	2B tok	B3	63.9	93.1	-	70.2
	2B tok	B4	93.7	88.2	-	66.2
	2B tok	B5	82.6	91.8	-	67.6
	2B tok	Mono	94.2	71.0	-	53.7
rus-eng	100M tok	B1	77.5	85.1	-	60.9
	100M tok	B4	77.7	76.8	-	55.9
	100M tok	B5	66.2	81.8	-	60.0
	100M tok	Mono	79.4	65.5	-	54.8
	2B tok	B1	90.9	94.5	-	70.0
	2B tok	B2	87.5	91.6	-	68.8
	2B tok	B3	62.4	92.6	-	69.1
	2B tok	B4	91.7	90.1	-	66.0
	2B tok	B5	85.0	91.4	-	66.1
	2B tok	Mono	91.5	64.3	-	52.5
spa-eng	100M tok	B1	85.2	84.0	-	62.0
	100M tok	B2	85.0	85.5	-	63.1
	100M tok	B3	77.1	87.5	-	63.7
	100M tok	B4	88.2	74.9	-	57.0
	100M tok	B5	79.4	84.9	-	62.7
	100M tok	Mono	89.8	71.8	-	54.9
	2B tok	B1	93.8	92.9	-	69.5
	2B tok	B2	93.5	92.5	-	69.9
	2B tok	B3	78.7	94.3	-	71.2
	2B tok	B4	94.6	88.4	-	66.9
	2B tok	B5	82.2	92.5	-	68.7
	2B tok	Mono	92.5	67.1	-	55.3

Pair	Data	Curr.	MultiBLiMP		MonoBLiMP	
			L1	Eng	L1	Eng
nld-eng	Human-scale	B1	87.6	80.8	76.8	69.1
	Human-scale	Mono	88.9	63.5	79.0	52.5
	100M tok	B1	88.4	88.1	74.5	63.9
	100M tok	B5	77.3	84.9	63.2	62.8
	100M tok	Mono	88.1	67.9	73.4	55.3
	2B tok	B1	94.4	94.4	78.3	72.8
	2B tok	Mono	95.5	77.0	81.9	60.6
	24B tok	B1	95.2	93.5	81.0	74.5
	24B tok	B2	93.7	94.4	81.2	74.4
	24B tok	B3	68.4	96.0	59.4	76.3
	24B tok	B4	95.7	91.8	82.1	71.6
	24B tok	B5	80.3	95.7	67.2	75.9
	24B tok	Mono	96.3	79.7	81.7	61.7
deu-eng	Human-scale	B1	86.9	80.5	-	65.5
	Human-scale	Mono	90.0	64.7	-	51.2
	100M tok	B1	88.6	87.7	-	63.6
	100M tok	B4	87.6	75.6	-	57.1
	100M tok	B5	75.2	83.0	-	62.7
	100M tok	Mono	89.3	67.0	-	52.4
	2B tok	B1	95.7	94.0	-	71.5
	2B tok	B3	92.3	73.0	-	54.3
	2B tok	Mono	96.0	73.9	-	55.3
	24B tok	B1	94.8	94.3	-	74.4
	24B tok	B2	94.2	93.6	-	74.2
	24B tok	B3	73.1	95.7	-	75.6
	24B tok	B4	96.4	92.6	-	70.4
	24B tok	B5	82.0	95.6	-	74.1
	24B tok	Mono	97.0	75.3	-	59.7

Pair	Data	Curr.	L1	MultiBLiMP		MonoBLiMP	
				Eng	L1	Eng	
zho-eng	Human-scale	B1	-	76.6	70.4	66.0	
	Human-scale	Mono	-	61.7	74.6	51.5	
	100M tok	B1	-	82.1	60.5	61.4	
	100M tok	B2	-	84.0	61.1	63.2	
	100M tok	B3	-	86.2	56.5	63.3	
	100M tok	B4	-	69.4	62.6	57.4	
	100M tok	B5	-	81.6	58.7	61.8	
	100M tok	Mono	-	68.4	64.6	53.0	
	2B tok	B1	-	91.7	75.9	70.9	
	2B tok	B2	-	92.9	73.7	71.6	
	2B tok	B3	-	93.9	55.9	72.7	
	2B tok	B4	-	89.6	76.2	67.3	
	2B tok	B5	-	89.5	67.5	69.1	
	2B tok	Mono	-	65.1	78.8	51.7	
	24B tok	B1	-	92.6	76.8	69.1	
	24B tok	B2	-	93.2	77.6	71.1	
	24B tok	B3	-	94.5	58.0	72.1	
	24B tok	B4	-	89.1	80.8	65.6	
	24B tok	B5	-	93.2	61.4	71.9	
	24B tok	Mono	-	64.2	78.8	53.6	
eng	Human-scale	Mono	-	79.0	-	64.7	
eng-nld	2B tok	B1	93.5	93.5	-	72.2	
eng-deu	2B tok	B1	93.6	93.6	-	71.6	

Table 7: Accuracy of Beetle models across curricula and L1s and data exposure (100, 2B, 24B) on L1 and L2 MultiBLiMP (Jumelet et al., 2025b) and Monolingual BLiMPs (English: BLiMP (Warstadt et al., 2020)); Dutch: BLiMP-NL (Suijkerbuijk et al., 2025a); Chinese: ZhoBLiMP (Liu et al., 2025b)

Model	Par.	Cohort	MultiBLiMP		MonoBLiMP	
			L1	Eng	L1	Eng
BLOOM-560M	0.56B	Dutch	59.8	81.7	52.6	66.7
		German	65.9	81.7		66.7
		Chinese		81.7	72.5	66.7
BLOOM-1.1B	1.1B	Dutch	63.0	92.5	48.7	76.7
		German	76.5	92.5		76.7
		Chinese		92.5	84.1	76.7
BLOOM-1.7B	1.7B	Dutch	66.4	93.0	48.7	76.4
		German	75.2	93.0		76.4
		Chinese		93.0	84.8	76.4
BLOOM-3B	3B	Dutch	66.3	94.8	51.1	74.2
		German	80.7	94.8		74.2
		Chinese		94.8	84.0	74.2
BLOOM-7.1B	7.1B	Dutch	64.0	94.0	55.5	77.5
		German	82.2	94.0		77.5
		Chinese		94.0	84.3	77.5
XGLM-4.5B	4.5B	Dutch	96.9	98.7	83.6	80.9
		German	98.8	98.7		80.9
		Chinese		98.7	84.6	80.9
EuroLLM-9B	9B	Dutch	76.4	84.4	88.0	79.6
		German	77.3	84.4		79.6
		Chinese		84.4	83.5	79.6
Gemma-3-270M	0.27B	Dutch	83.7	97.0	69.9	78.8
		German	90.4	97.0		78.8
		Chinese		97.0	80.7	78.8
Gemma-2-2B	2B	Dutch	91.7	98.7	80.5	76.5
		German	95.6	98.7		76.5
		Chinese		98.7	82.3	76.5
Gemma-2-9B	9B	Dutch	91.2	98.8	84.4	77.3
		German	96.4	98.8		77.3
		Chinese		98.8	82.9	77.3
Gemma-2-27B	27B	Dutch	78.6	82.6	74.0	70.7
		German	81.1	82.6		70.7
		Chinese		82.6	71.5	70.7
Qwen3-0.6B	0.6B	Dutch	81.5	97.0	71.7	81.6
		German	92.6	97.0		81.6
		Chinese		97.0	82.0	81.6
Qwen3-4B	4B	Dutch	93.9	99.5	82.6	82.8
		German	97.2	99.5		82.8
		Chinese		99.5	85.9	82.8
Qwen3-8B	8B	Dutch	94.6	98.7	82.1	82.5
		German	98.5	98.7		82.5
		Chinese		98.7	85.9	82.5
Llama-3.2-1B	1B	Dutch	90.8	99.0	76.0	81.8
		German	96.1	99.0		81.8
		Chinese		99.0	82.9	81.8
Llama-3.1-8B	8B	Dutch	96.1	99.2	85.1	81.2
		German	98.0	99.2		81.2
		Chinese		99.2	84.5	81.2

Table 8: Frontier multilingual-LLM baselines on L1 and L2 MultiBLiMP (Jumelet et al., 2025b) and Monolingual BLiMPs (English: BLiMP (Warstadt et al., 2020)); Dutch: BLiMP-NL (Suijkerbuijk et al., 2025a); Chinese: ZhoBLiMP (Liu et al., 2025b). *Par.* is the parameter count; *Cohort* is the evaluation language.