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MEG Evidence for Shared Neural Representations of Phrase Grammaticality Across Serial and Parallel Presentation

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Abstract

Language can occur in highly serial (speech) or fully parallel form (text), yet how our brains adapt to seriality differences is not understood. Here, we held modality constant (visual) and examined whether processing mechanisms underlying grammaticality detection are similar under Rapid Serial Visual Presentation (RSVP) and Rapid Parallel Visual Presentation (RPVP). To identify shared neural representations of grammaticality, we trained a classifier on magnetoencephalography (MEG) responses to grammatical and ungrammatical three-word phrases in one presentation mode and tested its generalization to the other. Behaviorally, accuracy was higher and reaction times faster for grammatical vs. ungrammatical phrases across presentation modes. Neurally, cross-presentation decoding revealed shared two-stage activity at word 2 across train-test directions, and an early shared representation at word 3 when trained on RPVP. We take the bidirectional representations at word 2 to capture combinatory processes and the asymmetry at word 3 as reflecting stronger global structure encoding in RPVP.

Keywords: Reading; grammaticality; Rapid Parallel Visual Presentation; Rapid Serial Visual Presentation; magnetoencephalography.

Introduction

Which aspects of language comprehension are shared across different degrees of seriality in the input? Serial presentation has enjoyed a privileged position in the study of the neurobiology of comprehension; speech is inherently serial, and decades of reading research has enforced seriality in the visual domain using Rapid Serial Visual Presentation (RSVP), which delivers words one-by-one. The popularity of serial presentation stems from its incremental nature, which permits scrutiny of subroutines associated with composition, and has led to detailed theoretical accounts of the mechanisms underlying language comprehension (e.g., Friederici, 2002, 2011; Hickok & Poeppel, 2007; Pylkkänen, 2019). In recent years, however, Rapid Parallel Visual Presentation (RPVP) has gained traction as an alternative way to present visual stimuli (Snell & Grainger, 2017). Here, short multi-word expressions are presented in their entirety for a few hundred milliseconds, with the absence of stimulus-internal temporal structure allowing linguistic computations to unfold in whatever order is natural for the system (Fallon & Pylkkänen, 2024). Instances of the so-called Sentence Superiority Effect show that the language system does indeed operate on the stimuli despite the rapid presentation: Grammatical sentences are identified faster and/or more accurately than word lists or scrambled sentences across a host of behavioral tasks (e.g., Fallon & Pylkkänen, 2024; Mirault et al., 2018; Pegado et al., 2021; Snell & Grainger, 2017). M/EEG studies have provided neural characterizations of the Sentence Superiority Effect, with activity diverging in left fronto-temporal areas as early as 130 ms post-stimulus onset and lasting several hundred milliseconds (Dufau et al., 2024; Dunagan et al., 2025; Fallon & Pylkkänen, 2024; Flower & Pylkkänen, 2024, 2026a; Krogh & Pylkkänen, 2025; Pegado et al., 2021; Wen et al., 2019, 2021). Most recently, a similar effect was observed with phrases (Li & Pylkkänen, 2026), suggesting it to reflect general *structure* superiority.

RSVP and RPVP both have their advantages and disadvantages. The word-by-word presentation of RSVP enables strict control of word processing, facilitating the detailed analysis of specific phenomena. To give just one example, a host of MEG studies have led to an extensive characterization of left anterior temporal lobe activity increases at 200 ms associated with basic composition (e.g., Bemis & Pylkkänen, 2011, 2013; Li & Pylkkänen, 2020; Parrish & Pylkkänen, 2022; L. Zhang & Pylkkänen, 2015). However, in experimental settings, RSVP reading can be quite unnatural; despite the "rapid" in its name, it is typically presented at around 600 ms per word, far slower than natural silent reading with eye movements (~230–250 ms per word; Brysbaert, 2019). Even within the RSVP literature, presentation rates as fast as 83 ms per word have been shown to allow comprehension and recall (Potter et al., 2014). As a result, slowly unfolding RSVP stimuli may elicit processing distinct from more natural language comprehension. For example, predictive processing, a central component of language processing (e.g., Brothers et al., 2015, 2023; Kuperberg et al., 2020; Lau et al., 2006, 2013; Szewczyk & Schriefers, 2018; Yano, 2018; W. Zhang et al., 2023), may be unnaturally enhanced, given the large amount of time to anticipate the next word. In contrast, RPVP eliminates prediction from temporally preceding context, enabling clean tests of the top-down effects of grammatical knowledge, with results so far revealing an early processing stage in which basic phrase structure is detected, but not yet agreement, semantic roles, or verb argument structure (Dunagan et al., 2025; Fallon & Pylkkänen, 2024; Flower & Pylkkänen, 2024; Krogh & Pylkkänen, 2025).

Given the complementary advantages of serial and parallel language presentation, and the need to understand how the language system flexibly accommodates both, it is important

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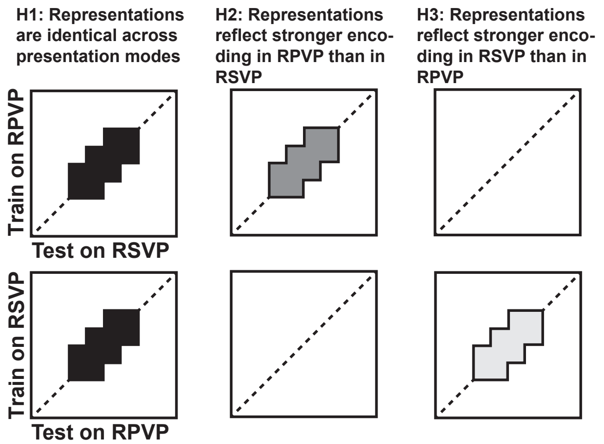

Figure 1: Hypothesis space. The different hypotheses need not apply uniformly to all word positions for RSVP. Diagonal clusters reflect shared, concurrent representations across presentation modes (illustrated here); off-diagonal clusters reflect shared but temporally shifted representations.

to characterize the extent to which stimuli with different temporal structures engage shared mechanisms. Here, we utilize similarity in neural representations as a method to investigate which linguistic computations are shared when three-word-phrases—semantically designed to address questions about animacy (not reported here)—are presented using RSVP and RPVP. To do so, we adopt a decoding approach of MEG data with generalization across time and presentation modes (King & Dehaene, 2014). Specifically, we trained classifiers to discriminate between neural responses to grammatical (e.g., `ARABIAN VALLEY TIGER`) and ungrammatical phrases (e.g., `VALLEY ARABIAN TIGER`) presented in one presentation mode, then assessed classifier performance when the same phrases were presented via the other presentation mode. Beyond providing the first direct comparison of RPVP and RSVP, the contrast between grammatical and ungrammatical phrases—as opposed to structured vs. unstructured stimuli as in prior RPVP studies—extends the extant RPVP literature to language processing gone awry.

The main advantage of our cross-presentation temporal generalization approach is that it captures shared patterns: Successful classification requires high rates of similarity across representations found in training and test data and thus likely reflects similar computations induced by both presentation modes. Moreover, the use of temporal generalization, rather than standard time-resolved decoding, allows us to probe for temporally asynchronous effects. Neural activation profiles between stimuli presented with RSVP and RPVP are expected to temporally diverge given the inherent differences in stimulus delivery timing and input structure, and it is therefore possible that representations are shared but have different latencies across presentation modes.

Our study entertains a complex hypothesis space, reflecting potential interactions between train-test directionality and serial word position (see Figure 1). If neural representations of grammatical and ungrammatical phrases are identical across presentation modes, we expect successful cross-presentation decoding regardless of train-test direction (H1). Alternatively, we may obtain unidirectional results if similar effects have different encoding strengths across the two presentation modes, leading to successful cross-presentation decoding when training on one presentation mode and testing on the other, but not vice versa. This could be the case for training on RPVP phrases and testing on RSVP phrases (H2) as well as for training on RSVP phrases and testing on RPVP phrases (H3). Since the three words in an RSVP phrase must be compared to the entire RPVP phrase one at a time, distinct patterns of results may emerge across word positions, consistent with different compositional subroutines at individual words. We expect shared neural representations of grammaticality to be particularly prominent at the second word, due to its central visual field position in RPVP, allowing us to probe cross-presentation representations at the exact point of composition (or the failure thereof).

Methods

Participants

37 native speakers of English completed the experimental protocol. All participants were neurologically intact with normal or corrected-to-normal vision. Participants provided their informed written consent and were paid for their participation. The study was approved by the Institutional Review Board (IRB) ethics committee of New York University (approval no. IRB-FY2024-8720). Eight participants were excluded from analyses (one for reporting a panic attack; one for sleepiness; six for excessive movement). This left 29 participants' data in the final dataset (16 female, 9 male, 4 nonbinary; 20-40 years old, mean age ± SD: 26.2 years ± 5.1 years).

Stimuli

Data reported in the present paper were obtained as part of a larger study that, in addition to characterizing phrase processing as a function of stimulus delivery technique, investigated the decodability of animacy in composed concepts. The study therefore employed a 2 × 2 × 2 factorial design with factors grammaticality (grammatical, ungrammatical), initial modifier type (geographical, material), and noun-noun order (location-animal, animal-location; see Table 1). For the noun-noun order manipulation, 25 animals and 25 locations matched for length and other lexical characteristics were identified and paired in two plausible but novel combinations (e.g., `TIGER` was paired with `VALLEY` and `DESERT`) as determined by transition probabilities of 0% in COCA (Davies, 2008–) and < 0.07% in iWeb (Davies, 2018) for both of the possible word orders (`VALLEY TIGER`; `TIGER VALLEY`). For the manipulation of initial modifier type, each of the 100 pairs was modified by one of ten geographical placenames (e.g., `ARABIAN`) and one of ten length-matched constitutive materials (e.g., `PLASTIC`), resulting in 200 grammatical three-word

Table 1: Design table (50 trials per condition). All stimuli were presented once using RSVP and once using RPVP.

Gram	Mod	N-N	Example
gram	geo	loc-ani	ARABIAN VALLEY TIGER
gram	geo	ani-loc	ARABIAN TIGER VALLEY
gram	mat	loc-ani	PLASTIC VALLEY TIGER
gram	mat	ani-loc	PLASTIC TIGER VALLEY
ungram	geo	loc-ani	VALLEY ARABIAN TIGER
ungram	geo	ani-loc	TIGER ARABIAN VALLEY
ungram	mat	loc-ani	VALLEY PLASTIC TIGER
ungram	mat	ani-loc	TIGER PLASTIC VALLEY

phrases. For the manipulation of grammaticality, ungrammatical phrases were formed by swapping the first two words in the grammatical phrases (grammatical: `ARABIAN VALLEY TIGER`; ungrammatical: `VALLEY ARABIAN TIGER`) for a total of 400 trials with 50 trials for each of the eight conditions. All stimuli were presented in all caps to avoid confounding effects from geographic placenames conventionally being capitalized. A full three-word phrase subtended a visual angle between 5.85° and 8.78° (mean ± SD: 7.29° ± 0.65°). Results obtained from the manipulation of initial modifier type and noun-noun order will be discussed elsewhere.

Experimental Design

The experimental protocol had four components: phrases presented in RSVP (4 blocks), phrases presented in RPVP (4 blocks), and single-word trials used to address questions reported elsewhere (10 blocks and 10 optional blocks). The 18 obligatory blocks were presented in a semi-structured, pseudorandomized manner following which participants could choose to do the 10 optional blocks. Here, we focus only on the two phrasal components in which participants read three-word phrases word-by-word (RSVP) or all-at-once (RPVP). Because all 400 three-word phrases were presented in both RSVP and RPVP, order of presentation was appropriately counterbalanced within and across participants.

Regardless of presentation mode, a trial always began with a fixation cross (200 ms) and a blank screen (200 ms; Figure 2). In RSVP, each of the three words in the phrase (target stimulus) was then presented for 300 ms followed by a 500 ms blank screen. In RPVP, the entire three-word phrase (target stimulus) was shown for 300 ms and followed by a 500 ms blank screen. Following prior RPVP-MEG studies, we used a simple matching task that has previously been shown to elicit Sentence Superiority Effects, providing evidence for an immediate and automatic effect of top-down grammatical knowledge despite the shallow nature of the task (Fallon & Pylkkänen, 2024; Flower & Pylkkänen, 2024, 2026a, 2026b; Dunagan et al., 2025; Krogh & Pylkkänen, 2025; Li & Pylkkänen, 2026). Regardless of presentation mode, trials thus concluded with a three-word task stimulus shown for 300 ms followed by a blank screen until button press. The task stimulus was either identical to the target stimulus (a match trial) or differed by one word (a mismatch trial). The position of the swapped word in the task stimulus was randomized across trials but the type of word (animal, location, geographical modifier, material modifier) and length were kept constant between target and task stimuli.

Procedure

Upon arrival to the lab, participants gave informed consent and filled out a brief demographic questionnaire. Then, 3D digitizations of participants' head shapes were recorded with a Polhemus FastSCAN laser scanner (Polhemus VT, USA) to enable coregistration of the MEG data with the FreeSurfer *fsaverage* brain (Fischl, 2012). The digitizations included five future marker coil placements and the location of three fiducial landmarks (nasion, left and right tragi). After a brief instruction period and practice sessions for all experimental components, participants were set up in the magnetically shielded room hosting the MEG machine and completed the experiment in supine position.

MEG Data Acquisition and Preprocessing

Continuous MEG data were recorded using a whole-head, 157-channel axial gradiometer system (Kanazawa Institute of Technology, Kanazawa, Japan) at a sampling rate of 1000 Hz with an online bandpass filter of 0.1–200 Hz. Participants' head positions relative to the MEG sensors were recorded before and after the experiment by means of marker coils. To ensure timing precision, a photodiode was used to measure stimulus-to-trigger delays.

In an initial preprocessing step, the Continuously Adjusted Least-Squares Method (Adachi et al., 2001) as implemented in the MEG160 software (Yokogawa Electrical Corporation and Eagle Technology Corporation, Japan) was used to noise-reduce the MEG data based on three reference channels. Subsequent preprocessing steps were undertaken in the Python computing environment using the *MNE-Python* v1.10 package (Gramfort et al., 2014) and included the application of a 1–40 Hz offline bandpass filter, interpolation of bad channels, and the use of Independent Component Analysis (ICA) to remove well-characterized non-neural artifacts. Epochs comprising the target stimulus and the ensuing blank screen were extracted for the three-word phrases presented in RPVP (800 ms) and in RSVP (2400 ms) and baseline-corrected using the 100 ms preceding the onset of (the first word in) the target stimulus. Individual epochs were rejected based on a 3000 fT peak-to-peak amplitude threshold or behavioral response anomalies (incorrect responses or response times more than 3 SDs from participant means). Finally, RSVP epochs were split into three 800-ms epochs (RSVP word 1, RSVP word 2, RSVP word 3) to allow for direct comparison with RPVP epochs. See Figure 3 for grand averages of the left-hemisphere sensors in RPVP and at each word in RSVP.

To enable faster computing and increase the signal-to-noise ratio (Grootswagers et al., 2017), we (1) downsampled epochs

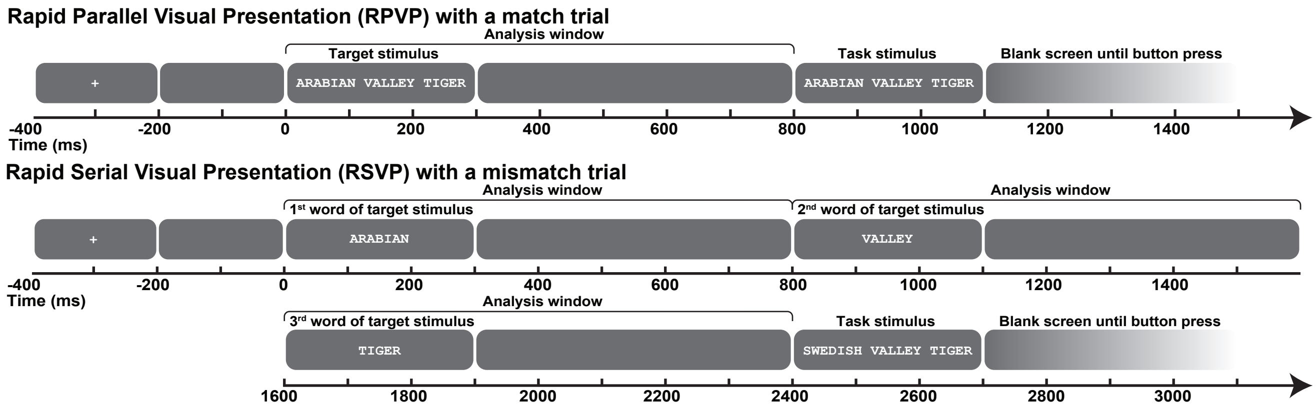

Figure 2: Trial structures for RPVP and RSVP trials illustrating a match and a mismatch trial. The data submitted to analysis only included the target stimulus (the entire three-word phrase in RPVP and individual words in RSVP), not the task stimulus.

by averaging non-overlapping bins of 5ms, (2) averaged two randomly sampled epochs from the same experimental condition without replacement, and (3) reduced the sensor space with Principal Component Analysis (PCA) from the 75 left-hemisphere sensors (midline sensors excluded) to 40 principal components explaining at least 96.65% of the variance. We restricted our analyses to the left hemisphere based on the left-lateralized results of earlier RPVP-MEG studies (Dufau et al., 2024; Fallon & Pylkkänen, 2024; Flower & Pylkkänen, 2024, 2026a; Krogh & Pylkkänen, 2025).

Behavioral Data Analysis

Responses with reaction times more than 3 SDs from a participant's overall mean were removed and the data subjected to (generalized) linear mixed effects regression models with grammaticality (grammatical, ungrammatical), presentation mode (RPVP, RSVP), and response type (match trial, mismatch trial) as fixed effects alongside all possible interaction terms. Response type was included as a fixed effect since match and mismatch trials were expected to differ in processing difficulty, a prediction that has been borne out in prior research using the matching task with RPVP (e.g., Fallon & Pylkkänen, 2024). The linear mixed-effects regression model of the reaction time data took log-transformed reaction time data (incorrect responses excluded) as the dependent variable and had by-participant and by-trial intercepts. The generalized linear mixed-effects regression model of the accuracy data (incorrect responses included) took accuracy as the dependent variable and had by-participant and by-trial intercepts as well as uncorrelated by-participant random slopes for response type, presentation mode, and their interaction. All p values were generated via likelihood ratio tests, and pairwise comparisons were corrected using a Tukey adjustment. Analyses were conducted using the *lme4* (Bates et al., 2015) and *afex* (Singmann et al., 2023) packages in R (v4.5.2) and RStudio (v2026.01).

MEG Data Analysis

Generalization across Time and Presentation Modes For our decoding analyses, we trained unique time-resolved decoders to discriminate between neural responses corresponding to grammatical and ungrammatical phrases in one presentation mode and tested their generalization to the other. This was done for each train-test combination of the RPVP epochs and the three RSVP epochs, resulting in a total of six tests. Our data were the 40 principal components derived from the MEG sensor data scaled to unit variance. Our model was a logistic regression classifier with l2 regularization for which regularization strength (C) was optimized via a grid search on a logarithmic scale between $1e^{-4}$ and $1e^{4}$ using stratified 5-fold cross-validation on the training data. Mechanistically, classification was done by training and testing separate unique classifiers on pairs of time points using 100-ms windows (with edge padding), stepped at 10-ms intervals throughout the epoch. Notably, we employed a 5-fold cross validation on our train-test data sets, emulating that used for within-set decoding, which will allow us to eventually compare cross-presentation decoding with within-presentation decoding (e.g., training and testing on RPVP phrases). The entire procedure was done separately for each subject.

Group-Level Statistical Testing Above-chance decoding at the group-level was assessed using cluster-based permutation tests (Maris & Oostenveld, 2007). For each analysis, group-level decoding accuracy at each pair of time points was evaluated against chance (0.5) using a one-tailed, one-sample t test, with resulting t values thresholded at those corresponding to an uncorrected p value of 0.05. Temporally adjacent pairs of time points were clustered using summed t values, and cluster significance was determined with Monte Carlo simulations (10,000 permutations). Only clusters with a size ≥ 2 points (equal to a minimum cluster duration of 20 ms) and a cluster p value ≤ 0.05 were retained. We restricted our group-level analysis window to train and test times between 100–500 ms since many combinatory processes are known to take place

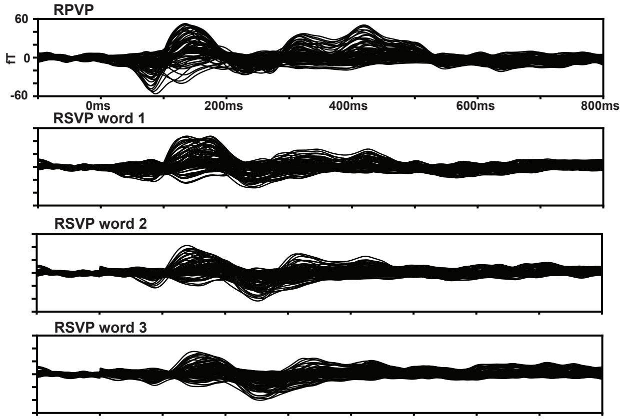

Figure 3: Grand averages of left hemisphere sensors across all participants for RPVP phrases and each word in RSVP. The baseline of RSVP word 1 is repeated for RSVP words 2 and 3 for visual comparison; baselines were not included in any statistical analyses.

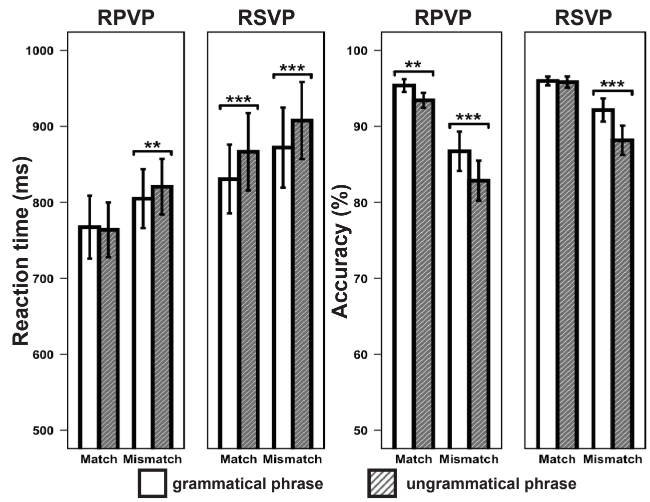

Figure 4: Behavioral sensitivity to grammaticality. Regardless of presentation mode, grammatical phrases enjoyed facilitated processing compared to ungrammatical phrases.

here in both RSVP and RPVP. The temporal extent of significant clusters should be interpreted with some caution since clusters are formed using uncorrected *t* values (Sassenhagen & Draschkow, 2019). All analyses were performed in the Python computing environment with the *MNE-Python* v1.0.3 (Gramfort et al., 2014) and *scikit-learn* v1.6.1 (Pedregosa et al., 2011) packages.

Results

Behavioral Sensitivity to Grammaticality Across Presentation Modes

We found clear processing advantages for grammatical over ungrammatical phrases, with main effects of grammaticality for both reaction time (p < .001) and accuracy (p < .001) as seen in Figure 4 and Table 2. In other words, participants responded faster and more accurately to grammatical phrases (815.65 ± 353.42 ms; 92.35 ± 6.46%) as compared to ungrammatical phrases (835.33 ± 359.45 ms; 89.98 ± 7.09%) across the entire dataset. In the case of reaction time, grammaticality interacted with presentation mode (p < .001), and while pairwise comparisons revealed the processing advantage to be significant only for RSVP (p < .001), it was still marginally significant for RPVP (p = .0591). In the case of accuracy, grammaticality participated in a two-way interaction with response type and a complete three-way interaction. Decomposition of the latter revealed processing advantages for grammatical over ungrammatical phrases in all pairwise comparisons but RSVP match trials (p = .9183; all other p < .0045).

We also observed main and interaction effects of response type and presentation mode across both reaction time and accuracy (all p < 0.001). Unsurprisingly, participants responded faster and more accurately to match trials than mismatch trials. Interestingly, however, the effects of presentation mode on reaction times and accuracies differed; participants responded faster to phrases presented with RPVP but had higher accuracies when phrases were presented with RSVP.

Shared Neural Sensitivity to Grammaticality, with Distinct Word Position-Profiles

Three of our six cross-presentation decoding analyses yielded significant clusters: successful bidirectional decoding at the second word as well as when training on RPVP and testing on RSVP word 3 (see Figure 5). Specifically, training on RPVP and testing on RSVP word 2 produced an early cluster (train: ~150–260 ms; test: ~230–380 ms; p = .0406) and a late cluster (train: ~320–500 ms; test: ~330–500 ms; p = .0256). The opposite train-test direction likewise yielded an early cluster (train: ~170–320 ms; test: ~150–310 ms; p = .0488) and a late cluster (train: ~330–490 ms; test: ~300–500 ms; p = .0109). A single early cluster arose from training on RPVP and testing on RSVP word 3 (train: ~100–230 ms; test: ~140–350 ms; p = .0338). The remaining cross-presentation analyses were not significant (all p > .11).

Discussion

In this direct comparison of RSVP and RPVP, we found behavioral and neural evidence for shared encoding of phrase grammaticality across presentation modes. Behaviorally, grammatical phrases had higher accuracies and faster reaction times compared to ungrammatical phrases (though the latter remained a trend for RPVP). Such sensitivity to grammaticality arose despite inherent differences in stimulus delivery timing and input structure as evidenced by the main effects of presentation mode: On average, RPVP trials elicited faster reaction times while RSVP trials had higher accuracy. Notably, the use of novel noun-noun compounds presented in all caps suggests that grammaticality detection does not depend on conceptual

Table 2: Likelihood ratio test results for linear mixed-effects regression models of reaction times and accuracies. gram: grammaticality; pres: presentation mode; resp: response type.

Effect	df	Reaction time		Accuracy	
		χ^2	*p* value	χ^2	*p* value
gram	1	23.37	<.001	16.72	<.001
pres	1	527.49	<.001	17.59	<.001
resp	1	307.43	<.001	21.70	<.001
gram × pres	1	12.51	<.001	0.88	.349
gram × resp	1	2.95	.086	4.98	.026
pres × resp	1	4.19	.041	1.69	.193
gram × pres × resp	1	1.41	.235	5.19	.023

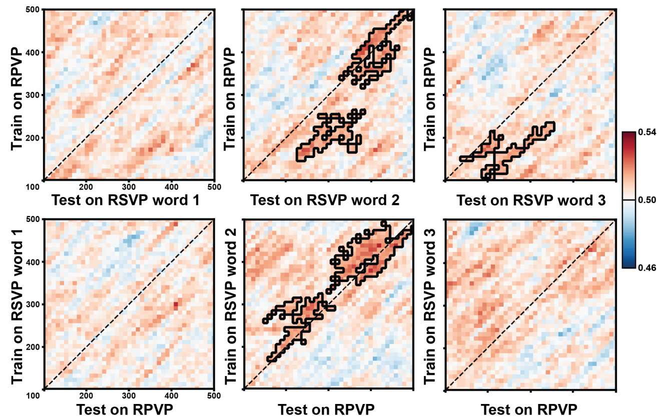

Figure 5: Cross-presentation decoding of grammaticality. Classification was successful in both train-test directions at RSVP word 2, each producing two clusters. Additionally, training on RPVP and testing on RSVP word 3 yielded an early cluster.

familiarity or recognizable visual envelopes cuing different word categories. Thus, behavioral sensitivity to grammaticality appears to arise from linguistic computations rather than some form of superficial mapping to phrasal templates.

By training a classifier on neural data from one presentation mode and evaluating its performance on the other, we directly assessed the representational invariance of grammaticality. This produced shared neural patterns across RPVP and RSVP, specifically a temporally similar two-stage activity at the second word in both train-test directions and an early, off-diagonal cluster when training on RPVP and testing on RSVP word 3. We interpret such shared representations to encompass more than mere visual encoding of the stimuli for two reasons. First, the lexical material at the first word varies across grammatical and ungrammatical phrases in just the same way as at the second word (ARABIAN VALLEY TIGER vs. VALLEY ARABIAN TIGER), yet effects were only observed at the latter. Second, we observed an effect at the third word despite identical lexical material across conditions (ARABIAN VALLEY TIGER vs. VALLEY ARABIAN TIGER), providing evidence that this shared representation must reflect the composite of combinatory operations.

The successful bidirectional decoding at the second word—the point where (un)grammaticality occured, not when it could be predicted—suggests that the signal at this point is dominated by presentation-invariant operations related to combining the first two words. Based on prior MEG-RSVP work, plausible candidates for such combinatory operations could be basic conceptual or syntactic composition at ~200 ms in, respectively, the left anterior or posterior temporal lobe, and a subsequent compositional integration stage at ~400 ms in left ventromedial prefrontal cortex (Pylkkänen, 2019, 2020). It is also possible that the late effect indexes integration difficulty, resembling N400 or P600 effects in EEG-RSVP studies (Kutas & Hillyard, 1980; Osterhout & Holcomb, 1992), but our stimuli's unusual grammatical violation (correct vs. incorrect order of adjectival and nominal modifiers) makes direct comparisons challenging. Notably, some instances of Sentence Superiority Effects observed in MEG-RPVP work also unfold in two stages (Flower & Pylkkänen, 2024; Krogh & Pylkkänen, 2025), further supporting the interpretation that certain compositional processes follow a consistent trajectory regardless of the input's temporal structure.

Unlike what we saw at the second word, cross-presentation decoding at the third word was asymmetric, succeeding only when training on RPVP and testing on RSVP, but not vice versa. This raises questions about why decoding succeeds in one direction but fails in the other. Since the third word marks the completion of stimulus presentation in RSVP, the observed shared representation may reflect the rapid encoding of global structure as also seen in prior MEG-RPVP work (Fallon & Pylkkänen, 2024; Flower & Pylkkänen, 2026a). It is possible that such global structure is encoded more strongly in RPVP than in RSVP because the simultaneous presentation of all three words enables immediate structure building or, perhaps, detection (see, e.g., Fallon & Pylkkänen, 2024; Dunagan et al., 2025; Flower & Pylkkänen, 2026a). Conversely, the slow unfolding of stimuli in RSVP may cause processes partially or fully absent in the RPVP representation to dominate the signal and therefore disrupt generalization in the reverse direction. We speculate that phrasal "wrap-up effects" could be one such process (Fodor & Bever, 1965; Just & Carpenter, 1980), reflecting delayed consolidation of the third word with the previous ones, but leave it to future research to explore this.

To conclude, we have demonstrated that sensitivity to grammaticality across RSVP and RPVP shares certain behavioral and neural characteristics. That we can find neural evidence for shared representations is striking given the vastly different temporal structures of the input. Used in tandem, RSVP and RPVP may thus provide a more comprehensive characterization of the neural underpinnings of language processing than either paradigm alone.

Acknowledgments

Cursor, an AI-assisted code editor, was used for modification and debugging of existing code.

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