Does entropy modulate the prediction of German long-distance verb particles?

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Abstract

In this paper we examine the effect of uncertainty on readers' predictions about meaning. In particular, we were interested in how uncertainty might influence the likelihood of committing to a specific sentence meaning. We conducted two event-related potential (ERP) experiments using particle verbs such as *turn down* and manipulated uncertainty by constraining the context such that readers could be either highly certain about the identity of a distant verb particle, such as *turn the bed [...] down*, or less certain due to competing particles, such as *turn the music [...] up/down*. The study was conducted in German, where verb particles appear clause-finally and may be separated from the verb by a large amount of material. We hypothesised that this separation would encourage

readers to predict the particle, and that high certainty would make prediction of a specific particle more likely than lower certainty. If a specific particle was predicted, this would reflect a strong commitment to sentence meaning that should incur a higher processing cost if the prediction is wrong. If a specific particle was less likely to be predicted, commitment should be weaker and the processing cost of a wrong prediction lower. If true, this could suggest that uncertainty discourages predictions via an unacceptable cost-benefit ratio. However, given the clear predictions made by the literature, it was surprisingly unclear whether the uncertainty manipulation affected the two ERP components studied, the N400 and the PNP. Bayes factor analyses showed that evidence for small a priori hypothesised effect sizes was inconclusive, although there was decisive evidence against large a priori hypothesised effect sizes greater than $1\mu V$ for the N400 and greater than $3\mu V$ for the PNP. We attribute the inconclusive finding to the properties of verb-particle dependencies that differ from the verb-noun dependencies in which the N400 and PNP are often studied.

Introduction

Contextual cues in a sentence preactivate words in memory, such that processing of those words begins before they are seen [1,2]. If contextual cues are sufficiently constraining, preactivation may crystallise into prediction of a specific word. Such lexical predictions can benefit readers in processing long-distance dependencies, where key information to interpreting an event is delayed [3–5]. Take for example the German particle verb construction in (1), where a large amount of material separates the verb “fuhr” *carried* from its particle “fort” *on*:

- (1) Der Professor **fuhr** mit seinem Vortrag trotz regelmäßiger
The professor **carried** with his lecture despite regular
Störungen **fort**.
interruptions **on**.

Rather than waiting for the particle to appear, and thus waiting to know the exact meaning of the sentence, readers may predict “fort” in order to facilitate processing of the intervening material. However, other plausible particles could include “ab” (*the professor drove off*), “zusammen” (*the professor was startled*), or “zurück” (*the professor reversed [his position] or drove back*). This creates uncertainty about the intended meaning of the sentence. In this paper, we use German particle verbs to test how uncertainty may affect predictive processing difficulty in long-distance dependencies. Although we did not find a conclusive answer to this question, we report our attempt as a resource for future researchers who may wish to revisit the issue. Furthermore, by reporting the inconclusive results, we avoid contributing to publication bias via the file drawer problem [6].

Prediction in long-distance dependencies

Evidence that readers make long-distance predictions is most often observed for syntactic information, including in verb-particle constructions. Piai et al. (2013) found evidence that Dutch verbs that could take a particle elicited a larger left anterior negativity (LAN) than those that never took a particle. The LAN has been associated with maintaining information in working memory [7], suggesting that the verb triggered a prediction for a particle. However, there was no evidence that the number of different particles licensed by the verb affected LAN amplitude, suggesting that the prediction was for the syntactic features of the verb-particle dependency and not for its lexical properties. The LAN effect was still present at the direct object, suggesting that readers maintained their syntactic prediction while processing the intervening sentence.

Further evidence for long-distance syntactic predictions comes from filler-gap dependencies such as *I know what_i you hit and broke the mirror with ___i* [8]. Encountering a transitive verb within a *wh*-dependency is argued to induce active prediction of a gap site, inducing longer reading times in the region of *hit*

than at the same point in the non-wh-dependency sentence *I know that you hit
and broke the mirror with the ball* [8–11]. This predicted gap is assumed to be
maintained until it is resolved. Evidence from event-related potentials (ERPs)
supports predicted gap maintenance by showing that a sustained anterior
negativity (SAN) is larger for *wh*-questions that are expected to be long vs.
short; this has been attributed to a higher burden placed on working memory
when a longer structure is expected [12–14].

Maintenance of a syntactic prediction should facilitate downstream
processing, and indeed such facilitation has been observed in reading times. For
example, encountering the word *either* facilitates processing of a co-ordinate *or*
structure in sentences like “The team took either the train or the subway...”
compared to “The team took the train or the subway...” [15,16]. This suggests
that *either* triggers a syntactic prediction for the co-ordinate structure, which is
sustained to facilitate reading at its resolution. Staub and colleagues also
observed that syntactic predictions facilitated processing by protecting against
misanalysis of S-coordination as NP-coordination. When *either* was present in
sentences such as “Either Linda bought the red car or her husband leased the
green one”, the NP *her husband* was never misanalysed as the direct object of
Linda bought. However, when *either* was absent, a strong preference for
NP-coordination appeared to trigger misanalysis, as suggested by a larger
number of regressions in the spillover region following *her husband*.
Long-distance syntactic predictions may therefore facilitate processing through
both preactivation and protection against misanalysis.

In contrast to syntactic prediction, lexical prediction may represent
commitment to a more specific sentence interpretation. Specific predictions can
increase the facilitatory advantage of a correct prediction, but also run an
increased risk of costly misprediction. The increased risk may explain why Piai
and colleagues (2013) did not find ERP evidence of lexical prediction in their
particle verb stimuli, as discussed above.

Commitment to a specific sentence interpretation refers to one account of the predictive mechanism in sentence processing where a specific interpretation might be stored in working memory [1, 2, 17, 18]. However, the mechanisms underlying predictive processing are by no means resolved. An alternative account is that the level of preactivation alone is sufficient to explain predictability effects [19]. This is supported by the success of metrics such as surprisal that measure the probability of a word given its context—which could be assumed to be linked to word preactivation—in accounting for variability in predictability-related empirical effects [20–25]. On the other hand, it has been shown that surprisal alone is not sufficient to explain all differences in reading times or the N400 [26, 27]. In the case of reading times, this was taken to suggest the need of an additional explanatory factors such as reanalysis or revision [26]. Assuming that reanalysis or revision can only be triggered if a commitment has been made, such findings could be taken as evidence that predictions can involve commitments.

On the other hand, reading time studies do provide some support for long-distance lexical predictions. A study of particle verb-like constructions in Persian found that increased lexical predictability of a head-final verb facilitated reading times in both short- and long-distance dependencies [4]. One interpretation of these results is that readers predicted the verb early in the sentence and sustained this prediction until it was resolved at the verb site. However, the pre-verbal information in both short- and long-distance conditions may have been informative about the identity of the verb, and so it is possible that the verb in this study was only predicted immediately prior to its being seen.

In similar constructions in Hindi, increased lexical predictability was also found to facilitate reading times at both short and long distance [3]. The pre-verbal region in this study was not informative about the identity of the verb, and so it could reasonably be concluded that the predictability effect in

the long-distance condition was evidence of long-distance lexical predictions. 98

In support of the Hindi findings, a study of German particle verbs found that 99
higher certainty about the identity of a particle facilitated eye fixation times at 100
the particle in both short- and long-distance conditions [5]. In this study again, 101
the pre-particle region was not informative about the identity of the particle, 102
supporting the conclusion that long-distance predictions may have been made. 103
However, the uncertainty effect was not replicated in self-paced reading times, 104
suggesting that the effect of lexical certainty on eye movements may have been 105
quite subtle. 106

Taken together, the above studies suggest that long-distance predictions are 107
generated and maintained to facilitate the processing of long-distance 108
dependencies. However, whether lexical content is included in these predictions 109
appears to be more difficult to observe. One possibility is that higher variability 110
among lexical versus syntactic continuations of a sentence creates a higher 111
degree of uncertainty for the parser. Combined with the likelihood that 112
intervening material may require the long-distance lexical prediction to be 113
reanalysed, lexical predictions may be discouraged in all but the highest 114
certainty situations. Even the potential facilitatory benefit of a correct 115
prediction to processing the predicted word and the intervening material may be 116
outweighed by potential reanalysis cost. 117

The cost of uncertainty in predictive processing 118

The probability of a misprediction increases as uncertainty about a sentence 119
increases, making uncertainty a potentially important factor in whether readers 120
make predictions about long-distance dependencies. A reader's uncertainty at a 121
given point in a sentence can be measured with entropy, which quantifies the 122
distribution of different ways a sentence could continue [20]; for example, via 123
the number of different continuations provided at a particular point in the 124
sentence in a sentence-completion task. A link between entropy and predictive 125

processing cost has been observed in reading times. Encountering a word that
triggers entropy among plausible sentence continuations has been associated
with longer reading times, suggesting that uncertainty creates processing cost
via the prediction and maintenance of multiple potential continuations in
memory [28, 29]. Large reductions in entropy have also been associated with
increased reading times, suggesting that large shifts in expectation also incur a
processing cost [20, 24, 30, 31].

The relationship between entropy and processing cost is less well-studied in
event-related potentials (ERP). Several experiments have examined the effect of
contextual constraint on predictive processing, and constraint can be interpreted
as a measure of entropy at a target region of a sentence. However, constraint in
such studies is usually quantified using the highest probability word given at the
target region in a sentence-completion task (a cloze test); for example, see
[32–34]. The degree of entropy among different cloze test completions is usually
not taken into account.

Entropy among cloze test completions is important if we assume that it
represents memory activations in a single reader [35]. Consider a sentence
where the most strongly activated word at a given point has a cloze probability
of 36% and that two other activated words each have a probability of 32% (high
entropy). A reader would be highly uncertain about how the sentence will
continue, given there are three almost equally probable options. Compare this to
a sentence where the strongest activated word also has a probability of 36%, but
where there is a large spread of other activated words each with a probability of
no more than 5% (lower entropy). The reader can now be relatively certain
about how the sentence will continue, even though the target word has the same
probability as in the first sentence. Under the highest-cloze-probability
definition of constraint used in many ERP studies, both sentences would be
grouped together as weakly constraining, even though the difference in
uncertainty will have different consequences for predictive processing.

The highest-cloze-probability definition of constraint may explain 155
inconsistency among ERP findings about the effect of constraint on processing 156
cost. In particular, studies have observed a larger anterior late positivity (PNP) 157
for unexpected words in strongly versus weakly constraining contexts, suggesting 158
that higher certainty leads to predictions which are more costly when 159
disconfirmed [32,33,36]. The PNP has been linked to the suppression of 160
disconfirmed sentence representations, potentially shedding light on the 161
mechanism driving the processing costs observed in reading times [37]. 162
However, not all studies of the PNP find an effect of constraint, or have 163
observed it in the opposite direction [34,38–42]. 164

Few studies have directly tested entropy in ERP, as opposed to constraint. In 165
an exploratory analysis of Thornhill and Van Petten’s (2012) data, a reduction 166
in entropy at the target word was found to explain some variance in the PNP, 167
although this did not survive a confirmatory analysis [23]. In Piai et al.’s (2013) 168
study of Dutch particle verbs, verbs that took large number of particles were not 169
found to elicit differences in the left anterior negativity (LAN) compared to 170
verbs that took a small number of particles. While entropy among particles was 171
not explicitly quantified, the findings can be interpreted as showing that 172
differences in lexical uncertainty did not result in differences in working memory 173
burden, as indexed by the LAN. The processing cost of disconfirmed predictions 174
in relation to entropy was not investigated. Given that uncertainty may be a 175
deciding factor in predictive processing of long-distance dependencies and that 176
ERP has the potential to reveal mechanisms driving processing cost, we 177
conducted two ERP experiments examining the effect of entropy on predictive 178
processing. 179

The current experiments 180

The aim of the experiments was to test whether lexical entropy would affect 181
readers’ willingness to predict a long-distance verb particle. We compared 182

sentences which required a particle to be semantically plausible, but varied in
how many different particles could complete the sentence. Since we were
specifically interested in the effect of entropy among the different particles’
lexical representations, it was strictly controlled: In the example experimental
item (2) below, only a single particle was semantically plausible in conditions (a)
and (b). In conditions (c) and (d), at least two particles were plausible. We
hypothesised that readers should experience more uncertainty about the
meaning of the sentence in (c/d), and thus be less likely to predict a specific
particle given the increased potential for a misprediction and its associated cost:

(2) **1 plausible particle, expected:**

- a. Der ordentliche Professor **fuhr** mit seinem Vortrag trotz
The orderly professor **carried** with his lecture despite
regelmäßiger Störungen immer ordnungsgemäß **fort**, da er für
regular interruptions always properly **on**, as he for
seine Unaufgeregtheit bekannt war.
his unflappability known was.

1 plausible particle, violation:

- b. *Der ordentliche Professor **fuhr** mit seinem Vortrag trotz
The orderly professor **carried** with his lecture despite
regelmäßiger Störungen immer ordnungsgemäß **mit**, da er für
regular interruptions always properly **with**, as he for
seine Unaufgeregtheit bekannt war.
his unflappability known was.

2+ plausible particles, expected:

- c. Der ordentliche Buchhalter **fuhr** seinen zuverlässigen
The orderly accountant **turned** his reliable
Computer bei der Arbeit immer ordnungsgemäß **herunter/hoch**,
computer at work always properly **off/on**,
da er für seine korrekte Arbeitsweise bekannt war.
as he for his correct work practices known was.

2+ plausible particles, violation:

- d. *Der ordentliche Buchhalter **fuhr** seinen zuverlässigen
The orderly accountant **turned** his reliable

Computer bei der Arbeit immer ordnungsgemäß **mit**, da er für 206
computer at work always properly **with**, as he for
seine korrekte Arbeitsweise bekannt war. 207
his correct work practices known was.

We used the N400 and the post-anterior positivity (PNP) to measure 208
processing cost at the particle. In particular, we were interested in ERP 209
evidence of processing cost when an unexpected, semantically implausible 210
particle was encountered in conditions (b) and (d). We focused our inference on 211
these conditions because the target particles both had a cloze probability of zero. 212
This allowed us to rule out the possibility that any ERP difference observed at 213
the particle was due to differences in cloze probability, which correlate strongly 214
with amplitude of the N400 and the PNP [33, 43]. While cloze probability is a 215
measure of a word’s predictability, it does not necessarily equate to whether a 216
word is predicted: Preactivation of a word by its context—which increases cloze 217
probability [35]—also makes that word easier to access in the lexicon and 218
integrate into the building sentence representation once it is seen, without it 219
having been specifically predicted.¹ Differences in ERP amplitude associated 220
with a target word’s cloze probability may therefore also be driven by 221
non-predictive processes triggered by having seen that word. In contrast, a 222
difference between two target words with the same cloze probability but 223
differing in entropy—the distribution of words not seen but 224
preactivated—should be informative about predictive processing. The target 225
words in (b) and (d) were always identical, and the pre- and post-critical regions 226
were matched between conditions to rule out any influence of the preceding or 227
following words on the ERP. The pre-critical region was not informative about 228
the identity of the particle. 229

We use the term “zero probability” when referring to the implausible 230
particles to reflect the fact that the sentence context is highly unlikely to 231

¹We assume a difference between preactivation and prediction, where preactivation can reflect activation of several different items in memory, while prediction reflects commitment to one specific item, for example by adding it to working memory [1, 2, 17, 18].

preactivate implausible particles in memory as they would be meaningless in the
context. However, there exists evidence from the N400 demonstrating that
readers can be sensitive to differences within the very low end of the probability
spectrum, including for implausible words [25]. These activations are unlikely
to be captured by a cloze test and thus have a cloze probability of zero, but
their preactivation may still affect ERP amplitude. This would be a caveat to
our “matched zero probability” target particles. The contribution of very low
probability words to entropy and ERP amplitude needs future investigation, but
for the current study we use the term “zero probability” to refer broadly to a
situation where, for the purposes of studying the strength of people’s
probabilistic representations of the context of a sentence, the contribution of
preactivation from an implausible particle is effectively zero.

To detect the cost of violated predictions, we examined two ERP
components: the N400 and the anterior post-N400 positivity (PNP). The N400
is a negative deflection in the ERP occurring at around 250–500 ms after a word
is seen and is highly correlated with a word’s probability given the preceding
sentence context [43]. Amplitude of the N400 decreases at each new,
context-congruent word in a sentence [44, 45] and increases at any unexpected
word, inversely proportional to its probability [43, 46]. This has led to the
hypothesis that sentence context allows the preactivation of probable words that
are then easier to process once encountered, and that the N400 reflects the
lexical access or update cost incurred by words with low preactivation [43, 47].

Previous studies involving uncertainty have tested the effect of contextual
constraint on the N400, but have not found that constraint affects its amplitude
when the cloze probability of the target words is matched [32, 33, 41, 46, 48]; but
see [49, 50]. That is, two words with the same low probability will trigger N400s
of the same amplitude, even if one of them is found in a strongly constraining
context and the other in a weakly constraining context. Lexical access and
probabilistic update models of the N400 explain this as occurring because each

low probability word has received no preactivation, meaning that lexical access is
equally unfacilitated [43] or that the shift in model update is equally large [47].
This presents a testable null hypothesis for the current study: if the N400 is not
affected by constraint—which should reflect entropy—then we should not expect
to see a difference in N400 amplitude between 1- and 2+particle violations.
However, given that few previous studies of the N400 have directly tested
entropy, it is possible that we could see a larger N400 in the 1-particle condition
reflecting greater update or more difficult lexical access after a misprediction.

The PNP is a positive amplitude deflection in the anterior region of the scalp
in the 600-900 ms window [32, 33, 46]. The PNP appears to be functionally
distinct from the more well-known posterior P600 [32, 33], which has been
associated with conflict detection and repair processes [51–56]. In contrast to
the P600, the PNP has been associated with suppression of disconfirmed
sentence representations [33, 37] and appears only to be sensitive to plausible
but unexpected words, suggesting that suppression may only occur if there is a
viable, alternative way to update the event representation [32, 33, 57]. If this is
the case, we may not expect to see a PNP modulation by our implausible
particles.

However, in addition to inconsistent findings about the effect of constraint on
the PNP already mentioned [34, 38–42], the plausibility feature has only ever
been tested in verb-noun dependencies. A context-violating noun may be
implausible at multiple levels of representation (e.g. animacy, thematic role,
semantic), whereas our implausible particles present a purely semantic violation.
It is thus less clear how the PNP might be affected. If purely semantic violations
can elicit the PNP, we may see a higher cost (larger PNP) of having to suppress
a disconfirmed sentence representation at the violation particle in the 1-particle
condition than in the 2+particle condition. If not, then we may see no difference
associated with entropy if the PNP is not triggered by the implausible violations.

We tested these hypotheses in two ERP experiments: in Experiment 1, we

used the 2×2 design set out in example (2) to compare the effect of the implausible particles on the N400 and PNP, but also to confirm that the particles could elicit an N400 and PNP in the implausible versus plausible conditions. In Experiment 2, we attempted to replicate the findings of Experiment 1 using a simpler design with a larger number of participants and experimental items. Data, code, and materials for both experiments can be found at <https://osf.io/h75jm/>.

Experiment 1

Experiment 1 tested whether entropy would affect readers' predictions about an upcoming verb particle. We inferred that predictions had been made by measuring processing cost at prediction violations. We predicted that a larger N400 and PNP would reflect the greater cost of recovering from a mis-prediction in the 1-particle condition than in the 2+particle condition where a prediction was less likely. Experiment 1 was pre-registered at <https://osf.io/qbna2>; see also S1 Appendix.

Materials and methods

Participants

Fifty-four participants were recruited. The sample size was determined by recruiting as many participants as was possible during one university semester. Four participants were excluded due to a large number of their target EEG trials being contaminated by muscle and/or blink artefacts. This left a total of 50 subjects (6 male), with a mean age of 25 years (range: 17–40 years, $SD = 5$ years). In line with university policy, all participants were reimbursed for their time either financially or in the form of credit points toward their studies. All participants were right-handed German native speakers, with no known history of developmental or current language, neurological, or psychiatric disorder, and

had not participated in the cloze test. The study was conducted in line with the principles of the Declaration of Helsinki and all participants provided written consent to participation in the study. In accordance with German law, IRB review was not required as the study involved only healthy adult participants.

Materials

For each particle verb, two sentences were constructed, as seen in Example (2). The position of the base verb and particle in each sentence pair was matched. The particle was the target word. Within each sentence pair, at least two words before the particle were identical. 103 sentence pairs were constructed and presented as a cloze test to 30 German native speakers (mean age 25 years, SD 6 years, range 18-41 years) on a desktop computer in our in-house lab using the Ibex software [58]. The sentence pairs were divided into two lists, such that each participant only saw one condition from each item. The particle of the sentence was replaced by a gap, which participants were asked to fill with the first word that came to mind.

The items were then ranked in terms of how well they fulfilled the criteria that the 1-particle condition elicited only one particle and the 2+particle condition elicited at least two particles with similar probability. To rank the items, cloze probabilities were calculated for each particle completion. Other kinds of completions were grouped into categories (e.g. prepositional phrases, adjectives, nouns) and a cloze probability was calculated for each category. Items were then ranked by entropy among the responses (lowest to highest in the 1-particle condition; highest to lowest in the 2+particle condition). For the 2+particle condition, further weight was given to items where the two highest ranked particles were close in cloze probability. This ranking scheme left a final set of 40 plausible items fulfilling the criteria of the experiment. Cloze probability and entropy statistics are summarised in Table 1.

To create the violation conditions, two German native speakers selected

Table 1. Cloze probability and entropy summary statistics for Experiment 1.

Condition	Cloze probability	Difference between	Entropy
	target particle Mean [95% CrI]	1st- and 2nd-best completion Mean [95% CrI]	target particle Mean [95% CrI]
1-particle	0.90 [0.74, 1.00]	0.73 [0.64, 0.85]	0.32 [0.31, 0.33]
2+particle	0.54 [0.53, 0.56]	0.29 [0.16, 0.39]	0.81 [0.80, 0.81]

1st- and 2nd-best completions refer to the highest and second-highest cloze particles at the target site.

particles that were not integrateable into the sentence context, including illicit
verb-particle combinations. No participant in the cloze test produced any of
these illicit particles. The same particle was used in both violation sentences
within each item. The 40 critical sentences used in the analysis were split into
four lists in a Latin square design, such that each participant only saw one of
the four conditions for each critical item and thus a total of 10 items per
condition. Critical sentences were pseudo-randomly interspersed with 98 filler
sentences. Sixty-two filler sentences contained plausible sentences in a variety of
lengths and tenses, some of which contained non-separated particle verbs (e.g.
hochgefahren, *switched on*). The remaining 36 fillers were particle verb
sentences from the cloze test that did not fulfill the 1- vs. 2+particle criteria. In
total, each participant saw a total of 138 sentences. The ratio of plausible to
implausible sentences was approximately 3:1. The order of presentation of
sentences within each list was pseudo-randomised via the presentation software.
Each sentence was followed by a yes/no question appeared that probed different
regions of the sentence; for example, the question for example (2) above was
“Verlief der Vortrag ungestört?” *did the lecture proceed uninterrupted?*.

Procedure

Participants sat in a shielded EEG cabin approximately 60 cm from a 56 cm
presentation screen. The experimental paradigm was built and presented using

Open Sesame [59]. Each experimental session began with an instruction screen advising participants that they would read sentences presented word-by-word and that after each sentence, they would answer a question using a video game controller. Participants were instructed to answer as quickly and accurately as possible. Each experimental session began with four practice trials.

Each trial in the experiment began with a 500 ms fixation cross in the centre of the screen followed by a blank screen jittered with a mean of 1000 ms and standard deviation 250 ms. Each sentence was presented word-by-word for a duration of 190 ms per word plus 20 ms for each letter. The target word was always presented for 700 ms regardless of length. The inter-word interval was 300 ms. A comprehension question appeared after each sentence and was answered via the video game controller, which triggered the next trial. Breaks were offered after every 30 sentences. The testing session including EEG setup lasted approximately two hours.

EEG recording and preprocessing

The EEG recordings were made in the Department of Linguistics at the University of Potsdam, Germany, in a purpose-built, electro-magnetically shielded EEG cabin using a 32-lead system and electrodes arranged on the head based on the international 10-20 system [60]. Electrode impedances were kept below $10\text{ k}\Omega$ throughout the experiment. EEG was recorded at a sampling rate of 512 Hz and online filtered with a low-pass filter of 138 Hz and using the left mastoid as a reference.

Raw EEG recordings were downsampled offline in BrainVision Analyzer 2, Version 2.1.2, to 500 Hz for ease of processing and interpretation. Zero phase shift IIR Butterworth filters were applied with a low-pass cut-off at 0.01 Hz (order of 2, time constant of 15.92) and a high-pass cutoff at 30 Hz (order of 2, no time constant). A notch filter was applied at 50 Hz. The full recording was then segmented into epochs from sentence onset to question onset. Ocular

correction using restricted Infomax was applied to the sentence epochs using
automatic independent component analysis (ICA) with a meaned slope
algorithm. The reference electrodes were two electrodes placed at the left outer
canthus and above the left eye to record horizontal and vertical eye movements,
respectively. The bound number of blinks was 60 with a convergence bound of
 10^{-7} . The number of ICA steps was 512. Components were found using sum of
squared correlations with the horizontal and vertical ocular electrodes [61–63].
The total value to delete was 30%.

The EEG was then re-referenced to the average of the two mastoids. The
corrected segments were further segmented into 1200 ms epochs representing a
period of 200 ms before the onset of the target word (the particle), and 1000 ms
after onset. EEG segments with muscle artefact or irreparable eye-blink or
movement artefact were automatically marked for 200 ms before and after each
respective artefact, defined as exceeding:

1. a maximum voltage step of more than $50 \mu V$
2. a maximum absolute difference of $200 \mu V$ in a 100 ms interval
3. a minimum amplitude of $-100 \mu V$
4. a maximum amplitude of $100 \mu V$
5. a minimum low activity of $1 \mu V$ in a 100 ms interval.

Marked segments were then visually inspected and discarded if they indicated
muscle artefact or a technical issue. This resulted in the exclusion of 6.20% of
the 1000 target trials used in the statistical analysis. A further 0.50% of trials
were excluded due to question response times over 10 seconds (indicating a
technical problem) and 0.30% were not recorded due to experimenter error. The
data were then exported and baseline-corrected in R using the package *eeguana*
[64].

Analysis

A linear mixed effects model with full variance-covariance matrices to account for the individual variability of subjects and items was fit to data from the violation conditions (b) and (d) using the *brms* package for R [65]. The dependent variable for the N400 was mean amplitude across the electrodes Cz, Pz, CP1, and CP2 in the 250–500 ms time window. The dependent variable for the PNP was mean amplitude across the electrodes Fz, FC1, and FC2 in the 600–900 ms window. For Experiment 1, these regions were chosen post hoc after we deviated from the pre-registered single-electrode analysis (see S1 Appendix and S2 Appendix). The regions were generally consistent with the distribution of the N400 and PNP observed in the predictive processing literature [32, 33, 66], although some studies observe a more anterior PNP [33, 36]. Since they were chosen post hoc, the regions of interest in Experiment 1 were used as pre-registered regions in Experiment 2.

The predictor ‘number of plausible particles’ was effect contrast coded to reflect our expectation for larger ERPs at 1-particle violations: 0.5 (1-particle), -0.5 (2+particle). The decision to use a categorical predictor rather than raw entropy was made because the precise functional relationship between entropy and ERP amplitude was not known, and we felt unable to safely assume it was linear.

To constrain the model to plausible values and avoid overfitting, we placed regularising priors of $N(0, 1)$ on each parameter [67–70]. This prior with a normal distribution centered on zero indicates to the model that, for example, the effect of the number of plausible particles will most likely be small or zero, with either a positive or negative sign, and has a 95% probability of lying between -2 and $2\mu V$.

To quantify how much evidence we had for any N400 and PNP effect, we conducted Bayes factor analyses comparing models with the predictor number of

particles (M1) versus a reduced model without this predictor (M0), i.e. BF_{10} . A Bayes factor of approximately 1 would indicate no evidence in favour of either model. As the Bayes factor increases over 3, evidence strengthens in favour of M1 [71, 72]. As the Bayes factor decreases under 0.3, evidence strengthens in favour of M0. Since the Bayes factor is sensitive to the choice of prior [73, 74], we conducted a sensitivity analysis by computing Bayes factors for a range of priors to determine how these affected our conclusions [75, 76]. We used a range of priors that assumed a priori effect sizes ranging from small, between -0.2 and $0.2\mu V$, to large, between -10 and $10\mu V$.

To confirm that the violation particles elicited an N400 and PNP relative to their plausible counterparts in line with previous studies [77], we fit the above models to all conditions (a-d) and added the predictor ‘plausibility’. Plausibility was effect contrast coded to reflect our expectation for larger ERPs in the implausible conditions: 0.5 (implausible), -0.5 (plausible) and a Bayes factor was computed at a prior of $N(0, 1)$. Since the plausible particles differed in cloze probability and identity from each other and from the violation particles, we used this analysis as a sanity check only and did not conduct any further analyses.

Results

Mean amplitude relative to the onset of the target particle is plotted in Figure 1. In Figure 1A-B, the 250-500 ms window of the ERP shows a strong negative deflection over the posterior scalp for the implausible conditions relative to the plausible conditions, consistent with an N400. Implausible particles also elicited a large positive deflection in the 600+ ms time window relative to plausible particles over the posterior scalp, consistent with a P600. Figure 1C-D shows a positive deflection in the post-N400 period of the ERP (i.e. after 500 ms) in fronto-central electrodes consistent with a PNP in the 1-particle condition relative to the 2+particle condition and relative to the plausible conditions.

Analysis of the N400

At implausible particles, the N400 was more negative in the 1-particle condition than in the 2+particle condition and the mean of the posterior was $-0.34 \mu V$ with a 95% credible interval (CrI) of $[-1.10, 0.39] \mu V$ (Figure 2A). The Bayes factor at a prior of $N(0, 1)$ favoured neither the null or alternative hypotheses about an entropy-related difference in the N400, $BF_{10} = 0.57$. The sensitivity analysis suggested there was moderate evidence against a priori hypothesised large effect sizes, but was inconclusive about small effect sizes (Figure 2B). There was strong evidence that the N400 was more negative for implausible than plausible particles, $\hat{\beta} = -1.09 \mu V, [-1.69, -0.48], BF_{10} = 465$.

Analysis of the anterior post-N400 positivity (PNP)

At implausible particles, the posterior mean indicated more positive amplitude in the 1- vs. the 2+particle condition, $\hat{\beta} = 0.74 \mu V$, 95% CrI $[-0.25, 1.77] \mu V$ (Figure 2C). However, the Bayes factor at a prior of $N(0, 1)$ favoured neither the null or alternative hypotheses about an entropy-related effect on the PNP, $BF_{10} = 1.50$. The sensitivity analysis suggested effect sizes of approximately $1 \mu V$ were more plausible than smaller or larger effects, although the Bayes factors even at $1 \mu V$ were inconclusive (Figure 2D). The PNP was more positive for implausible than plausible particles, although the Bayes factor suggested only anecdotal evidence for this conclusion, $\hat{\beta} = 0.49 \mu V, [-0.29, 1.24], BF_{10} = 2.69$.

Interim discussion

We compared sentence pairs where either a single verb particle or a small set of verb particles were plausible continuations given the context. We hypothesised that lower entropy would encourage commitment to a lexical prediction in the 1-particle condition, and that violating this prediction would be more costly relative to the 2+particle condition where higher uncertainty discouraged

Fig 1. Experiment 1: ERP results. **A.** Average amplitude following stimulus onset shows an N400 in the posterior region of interest (Cz, CP1, CP2, Pz) for violations of both the 1-particle (red) and 2+particle (blue) conditions relative to the plausible (grey) conditions. Ribbons show 95% confidence intervals. These intervals were calculated by fitting a linear model of the form *amplitude* ~ *condition* with by-subject and by-item intercept adjustments at each timestep of the ERP recording and extracting the standard error of the relevant conditions. The analysed N400 time window is overlaid. **B.** A voltage subtraction map of the N400 time window shows a small difference in amplitude between the 1-particle (a) and 2+particle (b) conditions in the region of interest (dashed square). **C.** A PNP for the 1-particle condition is seen in the anterior region of interest (Fz, FC1, FC2) 600-900 ms window after stimulus onset, but not in the 2+particle or plausible conditions. Ribbons show 95% confidence intervals. **D.** A voltage subtraction map of the PNP time window suggests amplitudes in the 1-particle condition were more positive in the mid-frontal region (dashed triangle) than in the 2+particle condition.

prediction. We predicted that this cost would be reflected in a larger N400 and
 PNP. Contrary to this prediction, evidence about the effect of entropy on both
 the N400 and PNP was inconclusive. The comparison of plausible versus

Fig 2. Experiment 1: Posterior estimates and Bayes factor analysis for the planned and exploratory comparisons. **A.** The posterior distribution represents the estimated change in N400 amplitude associated with violations in the 1-particle condition relative to the 2+particle condition. The point and errorbar reflect the posterior mean and 95% credible interval. **B.** Bayes factors computed under a range of priors comparing models with and without a predictor for the 1- vs. 2+particle condition manipulation. A Bayes factor of 1 indicates no evidence in favour of either model. Bayes factors below 1 indicate evidence against a difference in N400 amplitude associated with the manipulation. **C.** Posterior distribution of the difference in PNP amplitude between the violation conditions. **D.** Bayes factors under a range of priors for the PNP effect.

implausible particles elicited a difference in both component in line with the
typical plausibility effect observed in previous research, including research on
German particle verbs [77], confirming that the experiment worked in principle,
although evidence for the effect on the PNP was less conclusive than expected.

While Bayes factor evidence for the effect of entropy on the N400 was
inconclusive, the magnitude of the effect was small, which could be considered
consistent with the null hypothesis of lexical access and probabilistic update
accounts [42, 43, 47]. Under these accounts, the N400 at zero-probability words
should not be affected by uncertainty caused by multiple activated words. One
caveat to this conclusion is that, if there were truly no N400 effect, one could
have expected stronger support for the null hypothesis from the Bayes factor

analysis, especially since the cloze probability manipulation was able to yield strong evidential support. One reason that the Bayes factor may not have been able to distinguish between the null and alternative hypotheses is that the study was not sufficiently powered to detect or rule out an effect of entropy. While the study had a sample size of 50—larger than many ERP studies in the literature—a small number of critical trials (10 per participant) likely led to a large amount of noise in the averaged ERP data.

Bayes factor evidence for the PNP was also inconclusive, but the effect size was larger and consistent in sign with previous findings on the effect of constraint (larger PNP for violations in high-constraint settings) [32,33,36]. This may suggest that lower entropy led to a prediction in the 1-particle condition, eliciting a higher suppression cost once this prediction was violated. Higher entropy in the 2+particle condition may have discouraged predictions, avoiding this cost. However, again, one could have expected stronger evidence from the Bayes factor. The findings would therefore also be consistent with a null effect in line with current PNP accounts suggesting that the component should not be sensitive to entropy if the input is implausible [33,57].

One possible explanation for the weak Bayes factors is that variability was introduced into the data by individual differences in dealing with the implausible verb particles. Particles are more syntactically and semantically ambiguous than the implausible nouns used in previous PNP research and participants may have tried to reanalyse them in different ways, while others made no attempts at revision. For example, an implausible verb particle such as *make [a story] *on* could potentially be revised as a preposition *make [a story [on the war in Iraq]]....* The fact that a large posterior P600 was also elicited by the violations may indicate that such a syntactic reanalysis was attempted.

However, any conclusions from Experiment 1 are limited by a small number of critical trials, even though the sample size was relatively large for an ERP study. To test whether a larger study would provide more conclusive evidence

for the PNP effect and against the N400 effect, we used the results of
Experiment 1 to pre-register a second experiment with double the number of
participants and more than double the number of experimental sentences.

Experiment 2

Experiment 2 sought to replicate the findings of Experiment 1 in a larger
sample, using a larger number of experimental items. Since Experiment 1
already confirmed the presence of the expected ERP components at plausible vs.
implausible particles, to further increase the probability of detecting an effect,
we removed the plausible conditions to create a two-condition design. This
meant that the implausible conditions could be split into two rather than four
lists, doubling the number of critical trials each participant would see. In line
with Experiment 1, we expected that we would *not* see a difference in N400
amplitude between 1-particle and 2+particle violations, but that the PNP might
be larger in the 1-particle than the 2+particle condition. Experiment 2 was
pre-registered at <https://osf.io/y6k2d>; see also S1 Appendix.

Methods

Participants

Recruitment, inclusion, and exclusion criteria were identical to those in
Experiment 1. To estimate a suitable sample size for Experiment 2, we
conducted a power analysis using the data from Experiment 1. Although
Bayesian analysis was used for the main analysis, we conducted a frequentist
power analysis as it was computationally lighter and serves as a quick ballpark
estimate of the sample size needed for obtaining high-precision estimates [78].
The power analysis suggested that even with 300 participants we would only
achieve around 70% power. Due to resource constraints, it was only feasible to
collect data from around 100 participants. We therefore set a goal of 100

participants as the maximum feasible sample size and redid the power analysis, 569
which estimated around 50% power at this sample size. While likely to be 570
underpowered, our goal with Experiment 2 was to provide higher-precision 571
estimates of the effects observed in Experiment 1 using an improved design, and 572
to see to what extent doubling the size of the experiment would improve our 573
ability to quantify evidence for our hypotheses. This information is useful to 574
future evidence synthesis and in determining how one might approach future 575
experiments. In total, 115 participants were recruited, 4 of whom were excluded 576
as they did not meet the inclusion criteria. A further 11 were excluded due to 577
technical problems with the EEG recording. This left a total of 100 participants 578
(24 male), with a mean age of 24 years (range = 18 to 35 years, SD = 4 years). 579

Materials 580

Having established in Experiment 1 that the implausible particles did elicit the 581
target ERP components relative to their plausible counterparts, for 582
Experiment 2 we increased power by having participants see one of the two 583
violation conditions from each item rather than one of the four total conditions. 584
The plausible conditions were replaced by a length-matched sentence for each 585
item that contained a separated verb-particle dependency with a plausible 586
particle. This filler served to maintain the ratio of plausible to implausible 587
particle verb sentences, and to serve as a sanity check. These fillers were not 588
analysed as they were otherwise unmatched with the implausible sentences. 589
Each participant thus saw either condition (b) *or* (d), *and* the length-matched, 590
plausible filler from each item. 591

The sentences from Experiment 1 were re-used, plus 11 new sentences 592
constructed using the same procedure as for Experiment 1. The new sentences 593
were selected from a pool of 20 cloze-tested with 30 native German speakers 594
(mean age 24 years, SD 5 years, range 18-38 years). To create an even number of 595
sentences, one of the new sentences replaced the lowest-ranked of the 40 items 596

from the original cloze test. This gave a total of 50 critical items, making a total
of 50 items (25 per condition) analysed in Experiment 2. Cloze probabilities and
entropy are summarised in Table 2.

Table 2. Cloze probability summary statistics for Experiment 2.

Condition	Cloze probability	Difference between	Entropy
	target particle	1st- and 2nd-best completion	target particle
	Mean [95% CrI]	Mean [95% CrI]	Mean [95% CrI]
1-particle	0.89 [0.73, 1.00]	0.73 [0.64, 0.84]	0.31 [0.30, 0.32]
2+particle	0.53 [0.52, 0.55]	0.28 [0.15, 0.38]	0.81 [0.80, 0.81]

1st- and 2nd-best completions refer to the highest and second-highest cloze
particles at the target site.

In addition to the 50 target items and 50 matched fillers presented to
participants, 108 general filler sentences were randomly interspersed. These were
62 of the fillers from the Experiment 1 that did not contain separated particle
verbs, plus 46 new fillers, also not containing separated particle verbs. Overall,
each participant saw a total of 208 sentences during the testing session. The
ratio of plausible to implausible sentences was 4:1. Participants again answered
a yes/no question after each sentence.

Procedure, EEG recording, preprocessing

The data collection procedure and preprocessing were identical to that of
Experiment 1. EEG data cleaning resulted in the exclusion of 12.26% of the
5000 target trials due to artefact. A further 0.60% were excluded due to
question response times over 10 seconds and 0.32% were not recorded due to
experimenter error.

Analysis

The analysis comparing the two violation conditions for Experiment 2 was
identical to that of Experiment 1. The plausible filler was not analysed as there
were too many differences between these fillers and the critical items.

Results

Figure 3A-B show that the 250-500 ms window of the ERP showed a strong negative deflection in the implausible conditions relative to the plausible filler, consistent with an N400. A posterior P600 was elicited by implausible particles in the 600+ ms time window. Figure 3C-D also shows a positive deflection in the post-N400 period of the ERP (i.e. after 500 ms) in fronto-central electrodes consistent with a PNP, however this time in both the 1- and 2+particle conditions relative to the plausible filler, and most positive in the 2+particle condition.

Analysis of the N400

As for Experiment 1, there was a small between-condition difference in N400 amplitude at implausible particles, $\hat{\beta} = -0.22 \mu V$, 95% CrI $[-0.66, 0.22]$ Figure 4A, but the Bayes factor at a prior of $N(0, 1)$ favoured the null hypothesis that there was no effect of entropy on the N400, $BF_{10} = 0.35$. The sensitivity analysis indicated more conclusive evidence against a priori hypothesised large effect sizes than in Experiment 1, but was still inconclusive about small effect sizes despite the increased sample size Figure 4B

Analysis of the anterior post-N400 positivity (PNP)

The PNP effect at implausible particles appeared to have reversed relative to Experiment 1, with a more positive waveform in the 2+ than the 1-particle condition. The posterior mean indicated a small difference in amplitude between the violation conditions, $\hat{\beta} = -0.40 \mu V$, 95% CrI $[-0.89, 0.12]$ (Figure 4C). However, the Bayes factor at a prior of $N(0, 1)$ favoured neither the null or alternative hypotheses about an effect of entropy on the PNP, $BF_{10} = 0.84$. The sensitivity analysis this time indicated evidence against a priori hypothesised large effect sizes, but was even more inconclusive about smaller effect sizes than

Fig 3. Experiment 2: ERP results. **A.** ERP waveforms showing an N400 in 1-particle (red) and 2+particle (blue) in the posterior region of interest (Cz, CP1, CP2, Pz). Ribbons show 95% confidence intervals calculated as for Figure 1. The pre-registered time window of the N400 is overlaid. **B.** The voltage subtraction plot of the difference in amplitude between 1- and +particle violations in the N400 time window indicates very little difference in amplitude between the two conditions in the posterior region of interest (dashed square). **C.** ERP waveforms in anterior (Fz, FC1, FC2) region suggest that the most positive waveform in the pre-registered PNP time window (overlaid) was for 2+particle violations. Ribbons show 95% confidence intervals. **D.** The voltage subtraction plot of the difference in amplitude between 1- and 2+particle violations in the PNP time window suggests amplitude was more positive for 2+particle violations in the anterior region of interest (dashed triangle).

for Experiment 1 (Figure 4D).

In summary, despite the relatively large amount of data and a clean manipulation of entropy, no conclusive effect on the N400 or PNP was detected. Visual inspection of the ERPs did not point to any other effects of the manipulation.

Fig 4. Experiment 2: Posterior estimates and Bayes factor analysis for the planned comparisons. **A.** Posterior distribution of the estimated difference in N400 amplitude associated with 1-particle condition vs. 2+particle violations. The mean and 95% credible interval are overlaid. **B.** Bayes factors computed under a range of priors comparing models with and without a predictor for the 1- vs. 2+particle condition manipulation. A Bayes factor of 1 indicates no evidence in favour of either model. Bayes factors below 1 indicate evidence against a difference in N400 amplitude associated with condition. **C.** Posterior distribution of the difference in PNP amplitude between the violation conditions. **D.** Bayes factors under a range of priors for the PNP effect.

Discussion

Experiment 2 replicated the N400 findings observed in Experiment 1, with both violation particles eliciting an N400 of a similar amplitude regardless of whether one or more than one particle had been plausible in the context. Interestingly, the Bayes factor analysis did not become more conclusive with the increased sample size and number of trials, although the data were sufficient to rule out large effect sizes. The increased sample size and number of experimental stimuli may therefore still have been too small to yield conclusive evidence. This possibility is discussed further in the *General discussion*, as well as the relevance of the findings with respect to current models of the N400.

With respect to the PNP, the source of the reversal in effect direction relative

to Experiment 1 was unclear. The difference in sign could reflect oscillation
around a true mean of zero with a wide standard deviation. A true mean of zero
would be in line with current accounts of the PNP, which suggests that
implausible words such as our particles should not elicit an entropy-based
difference in amplitude. However, the inconclusive Bayes factor may suggest
that the data were too noisy to distinguish between the tested hypotheses at a
priori hypothesised small effect sizes, even though sensitivity analyses indicated
evidence against large effect sizes.

General discussion

In two experiments, we investigated whether uncertainty, as measured by
entropy, would influence readers' willingness to predict the lexical identity of an
upcoming particle in a long-distance verb-particle dependency. Experiment 1
suggested that predictions had been made when certainty was high, based on
the apparent cost of suppressing the disconfirmed sentence representation
indicated by a larger anterior post-N400 positivity (PNP). However, statistical
evidence was inconclusive and the effect was not replicated in the larger
Experiment 2. In Experiment 2, entropy did not appear to have an effect on
processing difficulty at the violations, although statistical evidence was again
inconclusive. We interpret the findings as related to how readers dealt with the
implausible verb particle.

Implausible input and the N400

The lack of conclusive evidence for an entropy-based N400 difference could be
interpreted as being consistent with current accounts of the N400, which would
not have predicted a difference [43,47]. This would further suggest that the
highest-cloze-probability definition of constraint used in the studies on which
these accounts are based is sufficiently similar to entropy, and that the

distribution of co-activated words is not an important factor in explaining N400
amplitude; at least not at an implausible word. Indeed, these accounts of the
N400 make no explicit predictions about how co-activated words should affect
processing of a zero-probability word; however, one could have imagined that
lexical access [43] or probabilistic update [47] might be dampened by the
presence of co-activations if these activations consume the same resources, or
create a large amount of uncertainty in the system. Co-activated words have in
fact been observed to modulate amplitude of the N400 at *plausible* but
unexpected words [38,42,47,79]. One contribution of the current study may
therefore be to confirm the implicit assumption of current N400 accounts that
uncertainty caused by competing lexical representations does not affect N400
amplitude if the input is implausible.

One caveat to any conclusion about the N400 in the current study is the
inconclusive Bayes factor analysis at small effect sizes. If the N400 is truly not
affected by constraint, then with sufficient data, one should have expected a
Bayes factor at least weakly in favour of the null hypothesis. While the data
were sufficient to find evidence against a priori hypothesised large effect sizes,
the inconclusive evidence against small effect sizes, even in the larger
Experiment 2, raises several possibilities: first, that some property of the
verb-particle violation differs to the types of violations in which the N400 is
usually studied and that this difference elicits a less clear-cut effect on the N400;
second, given a less clear-cut effect, that an even larger sample size would have
been needed to provide conclusive evidence against an entropy effect; or third,
that implausible words really did elicit a small difference in N400 amplitude
associated with entropy, but that the difference was too small to yield conclusive
evidence at the current sample size. We discuss the properties of the
verb-particle dependency next in relation to the PNP, in which the interaction
of plausibility and constraint (a proxy for entropy) has been directly tested in
previous research.

With respect to sample size, we again used a frequentist power analysis to gain a rough estimate of the sample size that would be needed for a hypothetical, future experiment using the same experimental design and assuming that the effect was the same size observed in Experiment 2 [80]. This prospective power analysis suggested that thousands of participants would be needed to achieve even 30% power, strongly suggesting that the above questions are likely not answerable with this particular design. Compare this to the power analysis conducted using the lower-precision estimates from Experiment 1, which vastly overestimated that we could achieve around 50% power with just 100 participants.

Entropy, implausibility, and the PNP

Previous findings suggest that constraint—similar to entropy—does not modify the PNP when the input is implausible [33, 57]. The lack of conclusive evidence for an entropy effect at implausible particles in the current study may therefore be consistent with the hypothesis that the PNP reflects only *successful* update of a mental sentence representation triggered by plausible input [33]. However, if the PNP is not elicited by implausible input, we should have expected conclusive evidence in favour of the null hypothesis, especially in the larger Experiment 2. It is therefore possible that something about the violation particle was different to the types of violations in which the plausibility effect on the PNP has previously been studied. Specifically, the implausible particle violates expectation at a purely semantic level of representation, since any syntactic expectation for ‘a particle’ was satisfied. In contrast, previous PNP studies have typically used verb-noun dependencies, where an implausible noun violates expectations at a number of levels of representation (e.g. animacy, thematic role, semantic). This raises the possibility that implausibility affects predictive processing cost in a graded way, with ‘lighter’ implausibility being simply less costly.

Alternatively, lighter violations may be more amenable to repair. In the current study, repair may have been aided by the fact that the verb-particle construction denotes a more abstract concept than a noun, which may allow attempts to update the semantic representation. For example, **carried with* is not a licensed verb-particle combination, but one could perhaps more easily invent a situation to accommodate it than to accommodate an implausible noun. Moreover, German particles are identical to prepositions and thus readers may have attempted to revise the particle as a preposition, e.g. *carried his lecture [with determination] on*. The large P600 in both experiments may suggest that such reanalysis was attempted [33,46,52,54,81–84].

In further support of a role of dependency type in modulating whether implausibility elicits the PNP, visual inspection of the ERPs in both experiments suggested that implausible particles did elicit a more positive waveform in the PNP window than plausible particles. Previous research in implausible nouns suggests that this should not have been the case [33,57]. However, the plausible and implausible particles in both experiments were not matched for frequency or lexical identity, and so this finding requires future investigation in a more controlled experiment. In summary, one possible explanation for the inconclusive findings in both the PNP and N400, despite the large sample size, is that the level of representation at which expectations are violated may be an important factor in using ERPs to measure how entropy affects predictive processing.

Entropy and the P600

While the P600 was not a focus of the current experiments and so was not analysed, its visual appearance in Figure 3 (Experiment 2) suggests that it was not affected by entropy. This contrasts with previous studies of anomalous words, where violations of strong constraint elicited larger P600s than violations of weak constraint [33]; for constraint effects at unexpected but still plausible words, see [85,86]. Kuperberg and colleagues propose that stronger constraint

makes the discrepancy between expected and received input larger, leading to a larger P600. This could suggest that the meaning discrepancy in the current study was not large enough to elicit a constraint effect.

However, there is another interesting possibility: that the violation occurred at different levels of representation between studies. Kuperberg and colleagues violated the animacy and thematic role constraints of expected nouns. In contrast, our particles violated only semantic constraints: there are no thematic roles or animacy features associated with particles, and although they could be reanalysed as prepositions, the morphosyntactic form of either a particle or preposition was not violated. Our P600 therefore contrasts with accounts of the P600 as a discrepancy between lexical expectations and expected morphologic form [81,85,87], as well as with accounts associating it with syntactic processing [51,54,88]. It is perhaps more consistent with accounts of the P600 as reflecting syntactic reprocessing attempts [89], general error detection and reanalysis process [83,90], or integration processes [52,55,56]. We leave to future research the question of whether the difference between our and Kuperberg and colleagues' violations suggest that violating different levels of representation affect the P600 differently.

Alternative accounts of ERP findings at the particle

Based on previous findings, we have attributed our inconclusive results to the difficulty of interpreting ERPs elicited by implausible words rather than to evidence that predictions were not made based on previous findings in particle verbs and similar constructions [3–5,91]. However, a non-prediction account is also compatible with the current findings. An integration account would propose that the lexical identity of the particles was not preactivated, but rather that processing was initiated once the particle was encountered in the input [92–94]. Being equally unintegratable into the sentence, an equal amount of processing difficulty would then be reflected in the amplitude of the ERP components. An

integration account could be contradicted by examining ERP differences earlier 798
in the sentence; for example, by examining whether working memory load 799
differed in line with whether a prediction had been made or not, as indexed by 800
the left anterior negativity (LAN) or sustained anterior negativity (SAN). 801
However, it is unclear whether the LAN is sensitive to working memory load 802
associated with lexical ambiguity as it is more often studied in relation to 803
syntactic structure building [12–14], although lexical ambiguity was found not 804
to play a role in one study [91]. An investigation of these components is beyond 805
the scope of the current article, but would be worthy of future examination to 806
further disentangle prediction from non-prediction accounts. 807

A second alternative account of our findings is that of Piai et al. (2013), who 808
concluded that the lexical representations of verbs that take particles—rather 809
than of the particles—are maintained in working memory to facilitate their 810
retrieval once the particle is encountered. Since the verbs should have been 811
equally retrievable, this would explain why no differences in ERP amplitude 812
were observed at the particle site. Our findings would also support the idea that 813
a syntactic placeholder for a particle was posited, in the same way that gaps are 814
posited in filler-gap dependencies [12–14], but that the lexical features of the 815
required particle were not activated until the particle was encountered. As 816
mentioned, there is some evidence from reading time studies to suggest that 817
entropy may influence the preactivation of long-distance lexical information 818
[3–5], but for now, ERP evidence remains elusive. 819

Conclusions 820

Using long-distance particle verb dependencies in German, we tested the 821
hypothesis that uncertainty may affect readers’ willingness to commit to a 822
specific sentence meaning. Long-range lexical predictions may be advantageous 823
to interpreting an event in German particle verb dependencies where the full 824

verb form can be split across almost an entire sentence. However, we were
unable to find conclusive evidence that uncertainty affected lexical predictions,
even in such a high-stakes context where predictions would have been
particularly useful. This result could have been due to the comparison of ERPs
at implausible target words; however, if this was the case, it is surprising that
evidence *against* an effect of uncertainty—as measured by entropy—was so
inconclusive given clear predictions made by the literature about implausible
input, and given that the study design was sufficient to demonstrate evidence
for a standard cloze probability effect on the N400.

We did find evidence, however, that manipulating entropy was unlikely to
produce changes in amplitude at large a priori hypothesised effect sizes. Thus,
our findings do not rule out the possibility that an entropy effect might be
present but small in magnitude. A small-magnitude entropy effect could suggest
that the semantic violation caused by an implausible verb-particle combination
has less clear consequences for processing cost than the violations at multiple
levels of representation caused by anomalous nouns in previous studies. This
raises questions such as whether simpler violations are less costly or whether
they are more amenable to repair. The properties of particle verb dependencies
therefore present an interesting way to extend our understanding of probabilistic
processing cost.

Supporting information

S1 Appendix. Detail on pre-registrations

Experiment 1 was pre-registered on OSF <https://osf.io/qbna2>.
Deviations from this pre-registration were: i) the number of critical trials
analysed was 40 and not 44 as pre-registered (4 items were excluded for not
meeting the criteria described under *Materials*); ii) we analysed a region of
electrodes rather than the pre-registered single electrode, as region analyses are

standard in the literature (see S2 Appendix for a comparison of the
single-electrode vs. region analysis results, in which our conclusions would have
been the same); iii) we used regularising priors with a standard deviation of
 $1\mu V$ ($Normal(0, 1)$) which assumed that ERP effects would vary with 95%
probability between $-2\mu V$ of zero. In contrast, the pre-registered priors had
standard deviations of 5 and even $10\mu V$, which are less plausible effect sizes
based on previous psycholinguistic ERP research. Moreover, regularising priors
better constrain the statistical model [67–70]; iv) we added hypotheses and
analyses concerning the PNP whose existence we were unaware of at the time of
the pre-registration; v) we used Bayes factors to quantify evidence for/against
effects rather than the pre-registered proportion of the posterior distribution
that was above zero, since the latter does not rule out a null effect or an effect
in the opposite direction if zero is a plausible value in the posterior [95].

Experiment 2 was pre-registered at <https://osf.io/y6k2d>. The deviations
to the pre-registration were: i) the number of critical trials was 50 rather than
54; ii) we used regularising priors rather than the same priors pre-registered in
Experiment 1; iii) we added Bayes factor analyses to inform inference.

S2 Appendix. Pre-registered single electrode analyses for Experiment 1.

The dependent variables for Experiment 1 deviated from the pre-registration
where we proposed analysing a single electrode as a way of reducing averaging,
which can artificially reduce variance [96]. However, the disadvantage of
analysing single electrodes is that ERP components are not so highly focal as to
appear at one electrode, and so the already high signal-to-noise ratio inherent in
ERP can drown out genuine effects or create the illusion of an effect where there
is none [97, 98]. For this reason, later in Experiment 2, we pre-registered and
analysed a region of electrodes based on the results of Experiment 1. To make
the presentation of results between both experiments consistent, we presented

Fig 5. Comparison the results of the pre-registered single-electrode analysis of the N400 in Experiment 1 with the region-based analysis presented in the main manuscript. Points and errorbars represent the means and 95% credible intervals estimated for the comparison of 1-particle and 2+particle violations in the N400 time window. Both analysis approaches yield comparable estimates, confirming that the region analysis used in the main manuscript did not lead to more (or less) favourable conclusions about the N400.

region analyses for both experiments. However, for transparency, we present here 880
a comparison of the posterior estimates obtained via the pre-registered, single 881
electrode analysis of Experiment 1 with those obtained via the region analysis. 882

Author contributions 883

KS and TM developed the idea and design of the experiment. KS oversaw 884
design of the stimuli and data collection. KS analysed the data with input from 885
TM and SV. KS wrote the manuscript with input from TM and SV. 886

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References

1. Kuperberg G, Jaeger TF. What do we mean by prediction in language comprehension? *Language Cognition & Neuroscience*. 2016;31(1). doi:10.1080/23273798.2015.1102299.
2. Pickering MJ, Gambi C. Predicting while comprehending language: A theory and review. *Psychological Bulletin*. 2018;144(10):1002–1044. doi:10.1037/bul0000158.
3. Husain S, Vasishth S, Srinivasan N. Strong expectations cancel locality effects: Evidence from Hindi. *PloS one*. 2014;9(7):e100986. doi:10.1371/journal.pone.0100986.
4. Safavi MS, Husain S, Vasishth S. Dependency resolution difficulty increases with distance in Persian separable complex predicates : Evidence against the expectation-based account. *Frontiers in Psychology*. 2016; p. 1–21. doi:10.3389/fpsyg.2016.00403.
5. Stone K, von der Malsburg T, Vasishth S. The effect of decay and lexical uncertainty on processing long-distance dependencies in reading. *PeerJ*. 2020;(8):e10438. doi:https://doi.org/10.7717/peerj.10438.
6. Rosenthal R. The file drawer problem and tolerance for null results. *Psychological Bulletin*. 1979;86(3):638–641. doi:10.1037/0033-2909.86.3.638.
7. Kutas M, Van Petten CK, Kluender R. Chapter 17 - Psycholinguistics Electrified II (1994–2005). In: Traxler MJ, Gernsbacher MA, editors. *Handbook of Psycholinguistics (Second Edition)*. London: Academic Press; 2006. p. 659–724. Available from: <https://doi.org/10.1016/B978-012369374-7/50018-3>.

8. Pickering MJ, Barton S, Shillcock RC. Unbounded dependencies, island constraints and processing complexity. In: Clifton C, Frazier L, Rayner K, editors. *Perspectives on sentence processing*. London: Lawrence Erlbaum.; 1994. p. 199–224.
9. Ness T, Meltzer-Asscher A. When is the verb a potential gap site? The influence of filler maintenance on the active search for a gap. *Language, Cognition and Neuroscience*. 2019;34(7):936–948.
doi:<https://doi.org/10.1080/23273798.2019.1591471>.
10. Wagers MW, Phillips C. Multiple dependencies and the role of the grammar in real-time comprehension¹. *Journal of Linguistics*. 2009;45(2):395–433. doi:10.1017/S0022226709005726.
11. Phillips C, Wagers MW, Lau E. 5: Grammatical Illusions and Selective Fallibility in Real-Time Language Comprehension. *Experiments at the Interfaces*. 2011; p. 147–180. doi:10.1163/9781780523750-006.
12. Fiebach CJ, Schlesewsky M, Friederici AD. Separating syntactic memory costs and syntactic integration costs during parsing: the processing of German WH-questions. *Journal of Memory and Language*. 2002;47(2):250–272. doi:10.1016/S0749-596X(02)00004-9.
13. Lau E, Stroud C, Plesch S, Phillips C. The role of structural prediction in rapid syntactic analysis. *Brain and Language*. 2006;98(1):74–88.
doi:10.1016/j.bandl.2006.02.003.
14. Phillips C, Kazanina N, Abada SH. ERP effects of the processing of syntactic long-distance dependencies. *Cognitive Brain Research*. 2005;22(3):407–428. doi:10.1016/j.cogbrainres.2004.09.012.
15. Staub A, Clifton C. Syntactic prediction in language comprehension: Evidence from either...or. *Journal of Experimental Psychology: Learning,*

- Memory, and Cognition. 2006;32(2):425–436.
doi:10.1037/0278-7393.32.2.425.
16. Frazier L, Clifton C. On Bound Variable Interpretations: The LF-Only Hypothesis. *Journal of Psycholinguistic Research*. 2000;29(2):125–140.
doi:10.1023/A:1005136826534.
 17. Ness T, Meltzer-Asscher A. Predictive Pre-updating and Working Memory Capacity: Evidence from Event-related Potentials. *Journal of Cognitive Neuroscience*. 2018;30(12):1916–1938.
doi:https://doi.org/10.1162/jocn_a.01322.
 18. Lau E. Neural Indices of Structured Sentence Representation: State of the Art. In: *Psychology of Learning and Motivation*. vol. 68. Elsevier; 2018. p. 117–142. Available from: <https://linkinghub.elsevier.com/retrieve/pii/S0079742118300045>.
 19. Staub A. The Effect of Lexical Predictability on Eye Movements in Reading: Critical Review and Theoretical Interpretation. *Language and Linguistics Compass*. 2015;9(8):311–327. doi:10.1111/lnc3.12151.
 20. Hale J. Uncertainty About the Rest of the Sentence. *Cognitive Science*. 2006;30(4):643–672. doi:10.1207/s15516709cog0000_64.
 21. Levy R. Expectation-based syntactic comprehension. *Cognition*. 2008;106(3):1126–1177. doi:10.1016/j.cognition.2007.05.006.
 22. Smith NJ, Levy R. The effect of word predictability on reading time is logarithmic. *Cognition*. 2013;128(3). doi:10.1016/j.cognition.2013.02.013.
 23. Frank SL, Otten LJ, Galli G, Vigliocco G. The ERP response to the amount of information conveyed by words in sentences. *Brain and Language*. 2015;140:1–11. doi:10.1016/j.bandl.2014.10.006.

24. Lowder MW, Choi W, Ferreira F, Henderson JM. Lexical Predictability During Natural Reading: Effects of Surprisal and Entropy Reduction. *Cognitive Science*. 2018;doi:10.1111/cogs.12597.
25. Szewczyk J, Federmeier KD. Context-Based Facilitation of Semantic Access Follows Both Logarithmic and Linear Functions of Stimulus Probability. *PsyArXiv*. 2021;doi:10.31234/osf.io/rbych.
26. van Schijndel M, Linzen T. Single-Stage Prediction Models Do Not Explain the Magnitude of Syntactic Disambiguation Difficulty. *Cognitive Science*. 2021;45(6):e12988. doi:<https://doi.org/10.1111/cogs.12988>.
27. Michaelov J, Bergen B. How well does surprisal explain N400 amplitude under different experimental conditions? In: *Proceedings of the 24th Conference on Computational Natural Language Learning*. Online: Association for Computational Linguistics; 2020. p. 652–663. Available from: <https://www.aclweb.org/anthology/2020.conll-1.53>.
28. Elman JL, Hare M, McRae K. Cues, Constraints, and Competition in Sentence Processing. In: *Beyond Nature-Nurture*. Psychology Press; 2004.
29. McRae K, Spivey-Knowlton MJ, Tanenhaus MK. Modeling the Influence of Thematic Fit (and Other Constraints) in On-line Sentence Comprehension. *Journal of Memory and Language*. 1998;38(3):283–312. doi:10.1006/jmla.1997.2543.
30. Linzen T, Jaeger TF. Uncertainty and Expectation in Sentence Processing: Evidence From Subcategorization Distributions. *Cognitive Science*. 2016;40(6). doi:10.1111/cogs.12274.
31. Frank SL. Uncertainty Reduction as a Measure of Cognitive Load in Sentence Comprehension. *Topics in Cognitive Science*. 2013;5(3):475–494. doi:<https://doi.org/10.1111/tops.12025>.

32. Federmeier KD, Wlotko EW, Ochoa-Dewald ED, Kutas M. Multiple effects of sentential constraint on word processing. *Brain Research*. 2007;(1146):75–84. doi:10.1016/j.brainres.2006.06.101.
33. Kuperberg G, Brothers T, Wlotko EW. A Tale of Two Positivities (and the N400): Distinct neural signatures are evoked by confirmed and violated predictions at different levels of representation. *Journal of Cognitive Neuroscience*. 2020;32(1):12–35. doi:https://doi.org/10.1162/jocn_a.01465.
34. Thornhill DE, Van Petten C. Lexical versus conceptual anticipation during sentence processing: Frontal positivity and N400 ERP components. *International Journal of Psychophysiology*. 2012;83(3):382–392. doi:10.1016/j.ijpsycho.2011.12.007.
35. Staub A, Grant M, Astheimer L, Cohen A. The influence of cloze probability and item constraint on cloze task response time. *Journal of Memory and Language*. 2015;82:1–17. doi:10.1016/j.jml.2015.02.004.
36. Brothers T, Wlotko EW, Warnke L, Kuperberg G. Going the Extra Mile: Effects of Discourse Context on Two Late Positivities During Language Comprehension. *Neurobiology of Language*. 2020;1(1):135–160. doi:https://doi.org/10.1162/nol_a_00006.
37. Kutas M. In the company of other words: Electrophysiological evidence for single-word and sentence context effects. *Language and Cognitive Processes*. 1993;8(4):533–572. doi:<https://doi.org/10.1080/01690969308407587>.
38. Federmeier KD, Kutas M. A rose by any other name: Long-term memory structure and sentence processing. *Journal of memory and Language*. 1999;41(4):469–495. doi:10.1006/jmla.1999.2660.

39. Wlotko EW, Federmeier KD. Finding the right word: Hemispheric asymmetries in the use of sentence context information. *Neuropsychologia*. 2007;45(13):3001–3014. doi:10.1016/j.neuropsychologia.2007.05.013.
40. Paczynski M, Kuperberg G. Multiple influences of semantic memory on sentence processing: Distinct effects of semantic relatedness on violations of real-world event/state knowledge and animacy selection restrictions. *Journal of Memory and Language*. 2012;67(4):426–448. doi:10.1016/j.jml.2012.07.003.
41. Lai MK, Rommers J, Federmeier KD. The fate of the unexpected: Consequences of misprediction assessed using ERP repetition effects. *Brain Research*. 2021; p. 147290. doi:10.1016/j.brainres.2021.147290.
42. Szewczyk JM, Schriefers H. Prediction in language comprehension beyond specific words: An ERP study on sentence comprehension in Polish. *Journal of Memory and Language*. 2013;68(4):297–314. doi:https://doi.org/10.1016/j.jml.2012.12.002.
43. Kutas M, Federmeier KD. Thirty Years and Counting: Finding Meaning in the N400 Component of the Event-Related Brain Potential (ERP). *Annual Review of Psychology*. 2011;62(1):621–647. doi:10.1146/annurev.psych.093008.131123.
44. Van Petten C, Kutas M. Interactions between sentence context and word frequency in event-related brain potentials. *Memory & Cognition*. 1990;18(4):380–393. doi:https://doi.org/10.3758/BF03197127.
45. Payne BR, Lee CL, Federmeier KD. Revisiting the incremental effects of context on word processing: Evidence from single-word event-related brain potentials. *Psychophysiology*. 2015;52(11):1456–1469. doi:10.1111/psyp.12515.

46. Van Petten C, Luka BJ. Prediction during language comprehension: Benefits, costs, and ERP components. *International Journal of Psychophysiology*. 2012;83(2):176–190.
doi:<http://dx.doi.org/10.1016/j.ijpsycho.2011.09.015>.
47. Rabovsky M, Hansen SS, McClelland JL. Modelling the N400 brain potential as change in a probabilistic representation of meaning. *Nature Human Behaviour*. 2018;2(9):693. doi:[10.1038/s41562-018-0406-4](https://doi.org/10.1038/s41562-018-0406-4).
48. Kutas M, Hillyard SA. Brain potentials during reading reflect word expectancy and semantic association. *Nature*. 1984;307(5947):161–163.
doi:<https://doi.org/10.1038/307161a0>.
49. Maess B, Mamashli F, Obleser J, Helle L, Friederici AD. Prediction Signatures in the Brain: Semantic Pre-Activation during Language Comprehension. *Frontiers in Human Neuroscience*. 2016;10.
doi:[10.3389/fnhum.2016.00591](https://doi.org/10.3389/fnhum.2016.00591).
50. Fleur DS, Flecken M, Rommers J, Nieuwland MS. Definitely saw it coming? The dual nature of the pre-nominal prediction effect. *Cognition*. 2020;204:104335. doi:[10.1016/j.cognition.2020.104335](https://doi.org/10.1016/j.cognition.2020.104335).
51. Hagoort P, Brown C, Groothusen J. The syntactic positive shift (sps) as an erp measure of syntactic processing. *Language and Cognitive Processes*. 1993;8(4):439–483. doi:<https://doi.org/10.1080/01690969308407585>.
52. Bornkessel-Schlesewsky I, Schlewsky M. An alternative perspective on “semantic P600” effects in language comprehension. *Brain Research Reviews*. 2008;59(1):55–73. doi:[10.1016/J.BRAINRESREV.2008.05.003](https://doi.org/10.1016/J.BRAINRESREV.2008.05.003).
53. Fitz H, Chang F. Language ERPs reflect learning through prediction error propagation. *Cognitive Psychology*. 2019;111:15–52.
doi:[10.1016/j.cogpsych.2019.03.002](https://doi.org/10.1016/j.cogpsych.2019.03.002).

54. Osterhout L, Holcomb PJ. Event-related brain potentials elicited by syntactic anomaly. *Journal of Memory and Language*. 1992;31(6):785–806. doi:10.1016/0749-596X(92)90039-Z.
55. Brouwer H, Crocker MW, Venhuizen NJ, Hoeks JCJ. A Neurocomputational Model of the N400 and the P600 in Language Processing. *Cognitive Science*. 2017;41(S6):1318–1352. doi:10.1111/cogs.12461.
56. Brouwer H, Hoeks JCJ. A time and place for language comprehension: mapping the N400 and the P600 to a minimal cortical network. *Frontiers in Human Neuroscience*. 2013;7. doi:10.3389/fnhum.2013.00758.
57. DeLong KA, Quante L, Kutas M. Predictability, plausibility, and two late ERP positivities during written sentence comprehension. *Neuropsychologia*. 2014;61(1). doi:<https://doi.org/10.1016/j.neuropsychologia.2014.06.016>.
58. Drummond A. Ibex: Software for psycholinguistic experiments; 2016. Available from: <https://github.com/addrummond/ibex>.
59. Mathôt S, Schreij D, Theeuwes J. OpenSesame: An open-source, graphical experiment builder for the social sciences. *Behavior Research Methods*. 2012;44(2):314–324. doi:10.3758/s13428-011-0168-7.
60. Jasper H. The 10/20 international electrode system. *EEG and Clinical Neurophysiology*. 1958;10(2):370–375.
61. Cardoso J. Blind signal separation: statistical principles. *Proceedings of the IEEE*. 1998;86(10):2009–2025. doi:10.1109/5.720250.
62. Makeig S, Bell AJ, Jung TP, Sejnowski TJ. Independent component analysis of electroencephalographic data. In: *Advances in neural information processing systems*; 1996. p. 145–151.

63. Bell AJ, Sejnowski TJ. An Information-Maximization Approach to Blind Separation and Blind Deconvolution. *Neural Computation*. 1995;7(6):1129–1159. doi:<https://doi.org/10.1162/neco.1995.7.6.1129>.
64. Nicenboim B. eeguana: A package for manipulating EEG data in R; 2018. Available from: <https://github.com/bnicenboim/eeguana>.
65. Buerkner PC. brms: An R Package for Bayesian Multilevel Models Using Stan. *Journal of Statistical Software*. 2018;80(1). doi:10.18637/jss.v080.i01.
66. DeLong KA, Urbach TP, Kutas M. Probabilistic word pre-activation during language comprehension inferred from electrical brain activity. *Nature neuroscience*. 2005;8(8):1117. doi:<https://doi.org/10.1038/nn1504>.
67. Gelman A. Prior Choice Recommendations; 2020. Available from: <https://github.com/stan-dev/stan>.
68. Chung Y, Gelman A, Rabe-Hesketh S, Liu J, Dorie V. Weakly Informative Prior for Point Estimation of Covariance Matrices in Hierarchical Models. *Journal of Educational and Behavioral Statistics*. 2015;40(2):136–157. doi:<https://doi.org/10.3102/1076998615570945>.
69. Gelman A, Jakulin A, Pittau MG, Su YS. A weakly informative default prior distribution for logistic and other regression models. *Annals of Applied Statistics*. 2008;2(4):1360–1383. doi:10.1214/08-AOAS191.
70. Gelman A, Simpson D, Betancourt M. The Prior Can Often Only Be Understood in the Context of the Likelihood. *Entropy*. 2017;19(10):555. doi:10.3390/e19100555.
71. Jeffreys H. *Theory of probability*. Clarendon; 1961.
72. Lee M, Wagenmakers EJ. *Bayesian Cognitive Modeling: A Practical Course*. Cambridge: Cambridge University Press; 2013.

73. Aitkin M. Posterior Bayes Factors. *Journal of the Royal Statistical Society: Series B (Methodological)*. 1991;53(1):111–128.
doi:10.1111/j.2517-6161.1991.tb01812.x.
74. Gelman A, Carlin J, Stern H, Dunson D, Vehtari A, Rubin B. Bayesian data analysis; 2013. Available from: <https://doi.org/10.1201/b16018>.
75. Lee M, Wagenmakers EJ. *Bayesian Cognitive Modeling: A Practical Course*. Cambridge: Cambridge University Press; 2014.
76. Schad DJ, Betancourt M, Vasishth S. Toward a principled Bayesian workflow: A tutorial for cognitive science. *Psychological Methods*. 2020;doi:<https://doi.org/10.1037/met0000275>.
77. Czipionka A, Golcher F, Błaszczak J, Eulitz C. When verbs have bugs: lexical and syntactic processing costs of split particle verbs in sentence comprehension. *Language, Cognition and Neuroscience*. 2019;34(3):326–350. doi:10.1080/23273798.2018.1539756.
78. Vasishth S, Yadav H, Schad D, Nicenboim B. Sample size determination for Bayesian hierarchical models commonly used in psycholinguistics. 2021;doi:10.31234/osf.io/u8yvc.
79. Szewczyk JM, Mech EN, Federmeier KD. Event-related potentials reveal rapid positive and negative updating of message-level representations. Potsdam; 2020.
80. Gelman A, Carlin J. Beyond Power Calculations: Assessing Type S (Sign) and Type M (Magnitude) Errors. *Perspectives on Psychological Science*. 2014;9(6):641–651. doi:<https://doi.org/10.1177/1745691614551642>.
81. Kim A, Osterhout L. The independence of combinatorial semantic processing: Evidence from event-related potentials. *Journal of Memory and Language*. 2005;52(2):205–225. doi:10.1016/j.jml.2004.10.002.

82. Kuperberg G, Sitnikova T, Caplan D, Holcomb PJ. Electrophysiological distinctions in processing conceptual relationships within simple sentences. *Cognitive Brain Research*. 2003;17(1):117–129.
doi:10.1016/S0926-6410(03)00086-7.
83. Meerendonk NVD, Kolk HHJ, Chwilla DJ, Vissers CTWM. Monitoring in Language Perception. *Language and Linguistics Compass*. 2009;3(5):1211–1224.
doi:<https://doi.org/10.1111/j.1749-818X.2009.00163.x>.
84. Metzner P, von der Malsburg T, Vasishth S, Rösler F. The Importance of Reading Naturally: Evidence From Combined Recordings of Eye Movements and Electric Brain Potentials. *Cognitive Science*. 2017;41.
doi:10.1111/cogs.12384.
85. Gunter TC, Friederici AD, Schriefers H. Syntactic Gender and Semantic Expectancy: ERPs Reveal Early Autonomy and Late Interaction. *Journal of Cognitive Neuroscience*. 2000;12(4):556–568.
doi:<https://doi.org/10.1162/089892900562336>.
86. Hoeks JCJ, Stowe LA, Doedens G. Seeing words in context: the interaction of lexical and sentence level information during reading. *Cognitive Brain Research*. 2004;19(1):59–73.
doi:10.1016/j.cogbrainres.2003.10.022.
87. van Herten M, Kolk HHJ, Chwilla DJ. An ERP study of P600 effects elicited by semantic anomalies. *Cognitive Brain Research*. 2005;22(2):241–255. doi:10.1016/j.cogbrainres.2004.09.002.
88. Osterhout L, Mobley LA. Event-Related Brain Potentials Elicited by Failure to Agree. *Journal of Memory and Language*. 1995;34(6):739–773.
doi:10.1006/jmla.1995.1033.

89. Friederici AD. The Time Course of Syntactic Activation During Language Processing: A Model Based on Neuropsychological and Neurophysiological Data. *Brain and Language*. 1995;50(3):259–281. doi:10.1006/brln.1995.1048.
90. Vissers CTWM, Chwilla DJ, Kolk HHJ. Monitoring in language perception: The effect of misspellings of words in highly constrained sentences. *Brain Research*. 2006;1106(1):150–163. doi:10.1016/j.brainres.2006.05.012.
91. Piai V, Meyer L, Schreuder R, Bastiaansen MCM. Sit down and read on: Working memory and long-term memory in particle-verb processing. *Brain and Language*. 2013;127(2):296–306. doi:10.1016/j.bandl.2013.09.015.
92. Brown C, Hagoort P. The Processing Nature of the N400: Evidence from Masked Priming. *Journal of Cognitive Neuroscience*. 1993;5(1):34–44. doi:10.1162/jocn.1993.5.1.34.
93. Van Berkum J, Hagoort P, Brown C. Semantic Integration in Sentences and Discourse: Evidence from the N400. *Journal of Cognitive Neuroscience*. 1999;11(6):657–671. doi:https://doi.org/10.1162/089892999563724.
94. Hagoort P. *Reflections on the Neurobiology of Syntax*; 2009.
95. Wagenmakers EJ, Lee MD, Rouder JN, Morey RD. The Principle of Predictive Irrelevance, or Why Intervals Should Not be Used for Model Comparison Featuring a Point Null Hypothesis. *Annals of Theoretical Psychology book series*. 2020;16:20.
96. Barr DJ, Levy R, Scheepers C, Tily HJ. Random effects structure for confirmatory hypothesis testing: Keep it maximal. *Journal of Memory and Language*. 2013;68(3):255–278. doi:10.1016/j.jml.2012.11.001.

97. Luck SJ. Ten Simple Rules for Designing and Interpreting ERP Experiments. In: Handy TC, editor. Event-related Potentials: A Methods Handbook. MIT press; 2005. p. 17–32.
98. Luck SJ, Gaspelin N. How to Get Statistically Significant Effects in Any ERP Experiment (and Why You Shouldn't). *Psychophysiology*. 2016;4424. doi:10.1111/psyp.12639.