Event-Related Potentials of the Semantically Informed Perception of Unfamiliar Objects

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Abstract

Abstract goes here.

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How does our perception of an object change as soon as we discover what it is for? In this study, we presented participants with unfamiliar objects, preceded either by valid information about their function (leading to semantically informed perception) or by misleading information (leading to naive perception). Capitalizing on the high temporal resolution of event-related potentials (ERPs), we investigated how different stages in the processing hierarchy are modulated by this semantic understanding of objects before, during, and after it has been acquired.

- One paragraph explaining that previous research has shown that semantic knowledge modulates early stages of visual perception (e.g. Abdel Rahman & Sommer, 2008; Gauthier et al., 2003; Maier & Abdel Rahman, 2019; Maier et al., 2014; Rossion et al., 2002, 2004; Samaha et al., 2018; Tanaka & Curran, 2001; Weller et al., 2019).

- Potentially one paragraph describing Abdel Rahman & Sommer (2008) in more detail (participants acquiring knowledge about existing but unfamiliar objects).

- One paragraph describing Samaha et al. (2018) in more detail (participants being trained to see familiar objects in otherwise meaningless images). Possibly hypothesize a special role of insight (= the moment when understanding is acquired), although this is not directly captured by the study.

- One paragraph explaining how all of these studies measured ERPs only *after* an extensive learning phase, making it difficult to determine (a) how much learning is necessary for semantic knowledge to influence perception and, related to that, (b) if the modulation of early ERP components reflects genuine online effects of semantic knowledge or rather the activation of altered visual representations (Firestone & Scholl, 2015) (?).

- One paragraph on theories of top-down/language effects on visual perception (reverse hierarchy theory).

- Possibly another paragraph on theories of top-down effects on visual perception (label feedback hypothesis) if it fits thematically.

- Do we need to refer to the role of attention already in the introduction? If so, potentially another paragraph here. I might prefer to leave that for the discussion.
- Possibly one more paragraph on why ERPs are so suitable to answer this research question, including a brief characterization of the relevant components (P1: lower-level visual perception, N1: higher-level visual perception, N400: semantic processing).
- The present study: Design of the study with a focus on distinguishing between online effects and altered representations; no specific hypotheses but looking for influences of semantic knowledge on the three ERP components at three different stages (before, during, and after acquisition).

Experiment 1

Methods

Participants

Participants for Experiment 1 were 24 German native speakers (13 female, 11 male) with a mean age of 24 years (range 18 to 31) and no history of psychological disorder or treatment. All participants were right-handed according to the Edinburgh inventory (Oldfield, 1971) and reported normal or corrected-to-normal vision. They gave written informed consent before starting the experiment and received a compensation of €8 per hour for participating. All experiments subsequently reported were carried out in accordance with the Declaration of Helsinki and approved by the local ethics committee.

Materials and Procedure

Stimuli for Experiments 1 and 2 consisted of 240 grayscale photographs of real-world objects, 120 of which were well-known everyday objects (e.g. a bicycle, a toothbrush), whereas the other 120 were rare objects presumed to be unfamiliar for the majority of participants (e.g. a galvanometer, an udu drum). The well-known objects were included as filler stimuli of no interest.

A list of the unfamiliar objects can be found in Appendix A. All stimuli were presented on a light blue background with a size of 207 × 207 pixels on a 19-inch LCD monitor with a resolution of 1,280 × 1,024 pixels and a refresh rate of 75 Hz. At a standardized viewing distance of 90 cm, the images of the objects subtended approximately 3.9 degrees of participants' horizontal and vertical visual angle.

For each unfamiliar object, a noun–verb pair was selected describing the object's typical function or use in a way that could typically be related to its visual features and their configuration (e.g. current–measuring, pottery–drumming). In the *insight* condition, the presentation of each unfamiliar object was preceded by its respective description, whereas in the *naive* condition, it was preceded by a non-matching description belonging to one of the other objects. In both conditions, the noun and the verb were presented one above the other in black letters on a light blue background. For each participant, half of the unfamiliar objects were presented in the insight condition (i.e. with a matching description) and the other half were presented in the naive condition (i.e. with a non-matching description). All participants saw each unfamiliar object in only one of the two conditions and the assignment of objects to conditions was counterbalanced across participants. The experiment was programmed and displayed using Presentation® software (Neurobehavioral Systems, Inc., Berkeley, CA, www.neurobs.com).

Each experimental session consisted of three parts (Figure 1A). In Part I, after written informed consent had been obtained and the EEG had been prepared, all 240 familiar and unfamiliar objects were presented once in random order and without verbal descriptions. Each trial consisted of a fixation cross presented in the middle of the screen for 0.5 s, followed by the presentation of the object until participants made a response or until a time out after 3 s. The inter-trial interval until the presentation of the next fixation cross was 0.5 s and participants took a self-timed break after each block of 60 objects. The task, which was kept the same throughout all parts and experiments, was to classify each object using one of four response alternatives: (a) "I know what this is or have a strong assumption," (b) "I have an assumption what this is," (c) "I have rather no assumption what this is," or (d) "I do not know what this is and have no assumption." Participants were asked to respond as quickly and as accurately as possible by pressing one out of four buttons with the index or middle finger of their left or right hand, respectively. The mapping of the rating scale to the four buttons (left to right or right to left) was counterbalanced across participants. Because we were interested in the acquisition of semantic knowledge about unfamiliar objects only, all objects for which the participant indicated knowing the object in Part I were excluded from further analysis (6.3% of rare objects per participant).

In Part II, only the 120 unfamiliar objects were presented for a second time, now preceded either by a matching verbal description (in the insight condition) or by a non-matching verbal description (in the naive condition). Each trial consisted of a fixation cross presented for 0.5 s, followed by the presentation of the verbal description for 2.5 s. Then, an asterisk was presented in the middle of the screen for another 0.5 s, followed by the presentation of the object until a response was made or until a time out after 3 s. The objects were presented in blocks of 30 trials so that within each block (a) there were 15 objects from each of the two experimental conditions and (b) objects were heterogeneous in terms of their shape, visual complexity, and functional category (e.g. medical devices, musical instruments). To make sure that insight did (did not) occur in the insight (naive) condition, we excluded any objects from the insight condition if participants indicated not knowing the object or having rather no assumption (despite reading the matching description) and any objects from the naive condition if participants indicated knowing the object or having an assumption (despite reading the non-matching description). This resulted in an average of 27.0 objects (44.9%) per participant remaining in the insight condition and an average of 48.8 objects (81.2%) per participant remaining in the naive condition.

In Part III, the unfamiliar objects were presented for a third time with an identical trial structure as in Part I, i.e. without the verbal descriptions. Note that Parts II and III were presented in an interleaved fashion so that after the presentation of one block of 30 objects in Part II (with descriptions), participants took a self-timed break and continued with the same block of 30 objects in Part III (without descriptions) before moving on to the next block consisting of 30 different objects. They continued like this until all four blocks were completed in both Parts II and III. In total, the experiment consisted of 480 trials (120 familiar objects in Part I and 120 unfamiliar objects in Parts I, II, and III) and took participants approximately 35

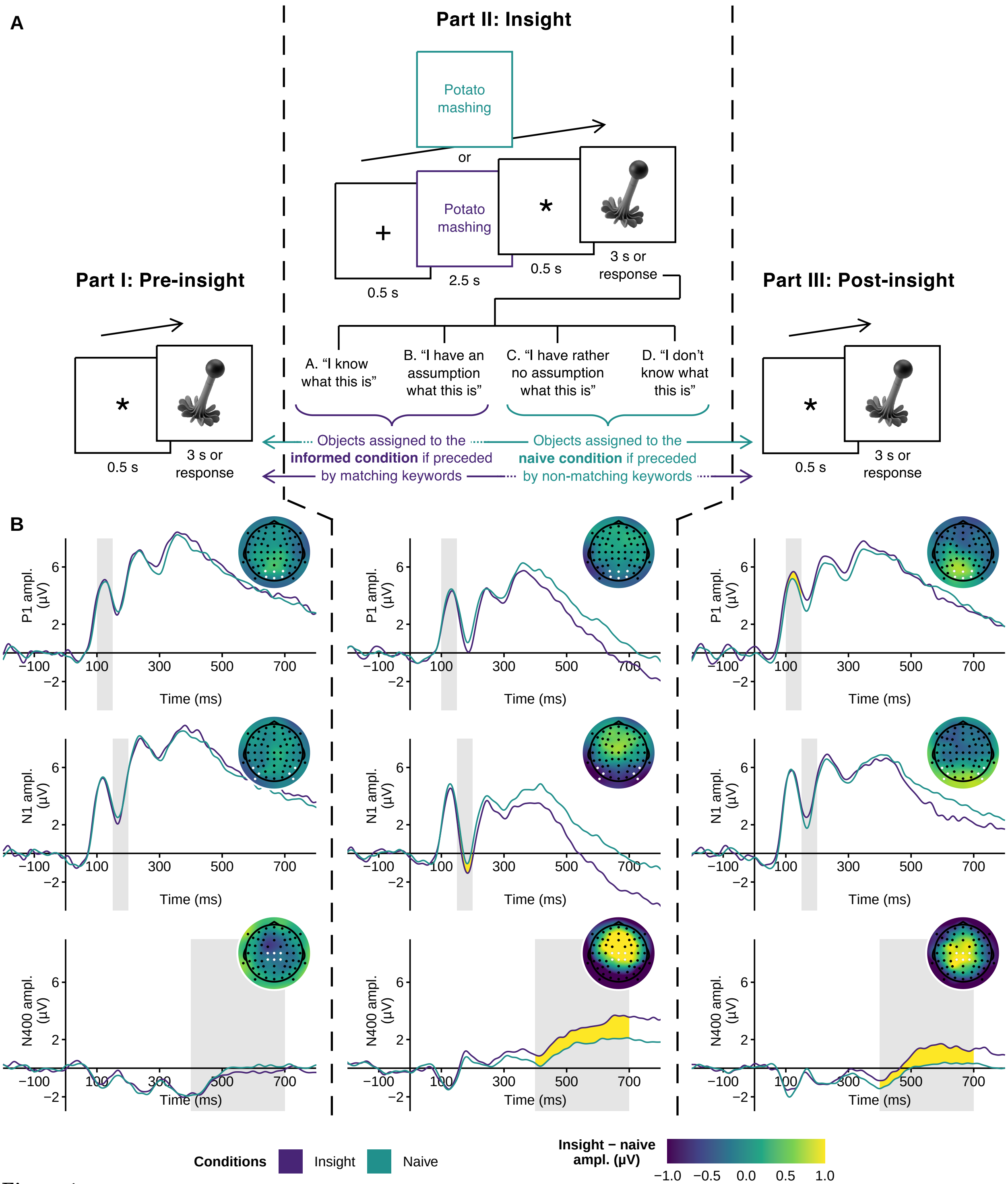

Figure 1

Procedure and results of Experiment 1. (A) *In Part I, participants were presented with 120 unfamiliar objects and indicated whether they knew what kind of object they were viewing. In Part II, half of the objects were preceded by a matching description (in purple color for illustration), leading to semantic insight, and the other half with a non-matching description (in petrol color for illustration), leading to naive perception. In Part III, the same objects were presented again without the descriptions.* (B) *Bar plots and* (C) *ERP waveforms and scalp topographies separately for objects for which participants experienced semantic insight and naive perception in Parts I, II, and III. Insight was associated with significantly more negative amplitudes in the N1 component in Part II, significantly less negative amplitudes in the N400 component in Parts II and III, and significantly more positive amplitudes in the P1 component in Part III. Error bars show the standard error of the mean. Ampl. = amplitude.* *p < .05. **p < .01. ***p < .001.

minutes to complete.

EEG Recording and Preprocessing

The continuous EEG was recorded from 62 Ag/AgCl scalp electrodes placed according to the extended 10–20 system (American Electroencephalographic Society, 1991) and referenced online to an external electrode placed on the left mastoid (M1). Two additional external electrodes were placed on the right mastoid (M2) and below the left eye (IO1), respectively. During the recording, electrode impedance was kept below 5 kΩ. An online band-pass filter with a high-pass time-constant of 10 s (0.016 Hz) and a low-pass cutoff frequency of 1,000 Hz was applied before digitizing the signal at a sampling rate of 500 Hz.

Offline, the data were preprocessed using the MNE software (Version 0.21.0; Gramfort et al., 2013) in Python (Version 3.7.7; van Rossum & Drake, 2009). First, all scalp electrodes were re-referenced to the common average. Next, artifacts resulting from blinks and eye movements were removed using independent component analysis (ICA). The first 15 components were extracted using the FastICA algorithm (Hyvärinen, 1999) after temporarily low-pass filtering the data at 1 Hz. Those components showing substantive correlations with either of two virtual EOG channels (VEOG: IO1 minus Fp1, HEOG: F9 minus F10) were removed automatically using the *find_bads_eog* function. After artifact correction, a zero-phase, non-causal FIR filter with a lower pass-band edge at 0.1 Hz (transition bandwidth: 0.1 Hz) and an upper pass-band edge at 30 Hz (transition bandwidth: 7.5 Hz) was applied. Next, the continuous EEG was epoched into segments of 2,000 ms, starting 500 ms before the onset of the visual presentation of each unfamiliar object. The epochs were baseline-corrected by subtracting the average voltage during the 200 ms before stimulus onset. Epochs containing artifacts despite ICA, defined as peak-to-peak amplitudes exceeding 200 µV, were removed from further analysis. This led to the exclusion of an average of 2.4 trials (0.7%) per participant (range 0 to 24). Single-trial event-related potentials were computed as the mean amplitude across time windows and regions of interests (ROIs) defined a priori, namely 100–150 ms after object onset at electrodes PO3, PO4, POz, O1, O2, and Oz for the P1 component, 150–200 ms after object onset at electrodes P7, P8, PO7, PO8, PO9, and PO10 for the N1 component, and 400–700 ms at electrodes C1, C2, Cz, CP1, CP2, and CPz for the N400 component.

Statistical Analysis

The event-related potentials were analyzed on the single trial level using linear mixed-effects regression models (Baayen et al., 2008; Frömer et al., 2018). For the purpose of the present study, these models have two desirable properties compared to more traditional approaches, such as analyses of variance (ANOVAs) performed on by-participant grand averages. First, they can account simultaneously for the non-independence of data points coming from the same participant or from the same item, whereas the neglect of the item as a random variable in ANOVAs leads to anti-conservative test statistics and strictly does not allow for inferences beyond the stimulus set under study (Bürki et al., 2018; Judd et al., 2012). Second, they can flexibly deal with unbalanced designs in which the number of trials differs across (combinations of) conditions, which is inevitable in designs where the assignment of trials to conditions is based on participants' own responses rather than on the experimental manipulation (e.g. Fröber et al., 2017).

Three separate models were computed predicting P1, N1, and N400 mean amplitudes, respectively. All models included three fixed effects: (a) the part of the experiment, coded as a repeated contrast (i.e. subtracting Part I from Part II and Part II from Part III, the intercept being the grand mean across all three parts), (b) the condition of the object, coded as a scaled sum contrast (i.e. subtracting the naive from the insight condition, the intercept being the grand mean across both conditions), and (c) the two-way interaction of part and condition. For details on these and other contrast coding schemes in linear (mixed-effects) models, please refer to Schad et al. (2020). To determine the random effects structure, we always started with a maximal model containing by-participant and by-item random intercepts and random slopes for all fixed effects (Barr et al., 2013). We then performed a model selection algorithm as proposed by Matuschek et al. (2017) for increasing statistical power and avoiding overparameterization: Iteratively, each random effects was removed and the resulting, more parsimonious model was compared to the previous, more complex model by means of a likelihood ratio test. Only if the parsimonious model explained the data equally well as the complex model (determined by $p >$ .20; Matuschek et al., 2017) did we leave the random effect out, otherwise it was kept in the final model. All models were calculated in R (Version 4.0.2; R Core Team, 2020) using the lme4 package (Version 1.1.23; Bates et al., 2015). The optimizer function *bobyqa* with $2 \cdot 10^5$ iterations was used for maximum likelihood estimation. The model selection algorithm via likelihood ratio tests was performed using the buildmer package (Version 1.7.1; Voeten, 2020). Finally, to answer our research question of whether or not semantic insight had an influence on the ERP components within each part, planned follow-up comparisons were calculated, contrasting the insight against the naive condition within Parts I, II, and III. Reported p values were computed by approximating the relevant denominator degrees of freedom using Satterthwaite's methods as implemented in the lmerTest package (Kuznetsova et al., 2017).

The materials and code for the present experiments can be accessed via the Open Science Framework (https://osf.io/…/).

Results

Single-trial ERPs were analyzed in response to unfamiliar objects before (Part I), while (Part II), and after (Part III) participants gained semantic insight into the function or use of the objects. Half of the objects were preceded by a matching description, fostering semantic insight to occur, whereas the other half were preceded by a non-matching description, leading to naive perception of the object. To make sure participants did indeed experience insight or naive perception, the analysis was constrained by participants' behavioral responses in Part II: Objects presented with a matching description were assigned to the insight condition only if the participant indicated that they understood what the object was (or had an assumption), whereas objects presented with a non-matching description were assigned to the naive condition only if the participant indicated that they did not understand what the object was (or had rather no assumption). The analysis focused on differences between the insight and the naive condition in the P1 component (100–150 ms) as an index of lower-level visual perception, the N1 component (150–200 ms) as index of higher-level visual perception, and the N400 component (400–700 ms) as an index of semantic processing.

Averaged across conditions, P1, N1, and N400 amplitudes differed as a function of the part

Table 1

Results of linear mixed-effects regression models for Experiment 1

	P1		**N1**		**N400**	
Fixed effects	F (df)	p	F (df)	p	F (df)	p
Part	10.89 (2, 24.5)	< .001	14.18 (2, 24.9)	< .001	32.85 (2, 25.6)	< .001
Insight	0.60 (1, 5343.5)	.438	0.30 (1, 24.2)	.586	13.00 (1, 24.4)	.001
Pt. × ins.	2.30 (2, 4605.1)	.100	4.84 (2, 4878.2)	.008	10.91 (2, 5120.9)	< .001
Insight − naive	Est. [95% CI]	p	Est. [95% CI]	p	Est. [95% CI]	p
Part I	-0.03 [-0.53, 0.47]	.913	-0.12 [-0.68, 0.44]	.665	-0.20 [-0.65, 0.26]	.400
Part II	-0.18 [-0.68, 0.32]	.490	-0.64 [-1.20, -0.08]	.026	0.93 [0.48, 1.39]	< .001
Part III	0.55 [0.05, 1.05]	.031	0.43 [-0.14, 0.99]	.136	1.00 [0.54, 1.46]	< .001

Note. Pt. = part, ins. = insight, est. = estimate, CI = confidence interval.

of the experiment, all Fs > 10.89, all ps $< .001$ (Table 1). In addition, N400 amplitudes differed between the insight and the naive conditions averaged across the three parts of the experiment, $F(1, 24.4) = 13.00$, $p = .001$. Crucially, the part × insight interaction was significant in the N1 component, $F(2, 4878.2) = 4.84$, $p = .008$, and in the N400 component, $F(2, 5120.9) = 10.91$, $p < .001$, while also being marginally significant in the P1 component, $F(2, 4605.1) = 2.30$, $p = .100$. To answer our main research question, we decomposed these interactions into the differences between the insight and the naive condition within the three different parts of the experiment.

Effects of Insight in Part I

In Part I, when objects were unfamiliar to the participant and presented without verbal descriptions, no differences emerged between the insight and the naive condition in the P1, N1, or N400 component, all ps $> .400$ (Table 1, Figure 1B & C). On the one hand, this was to be expected given that the critical presentation of the objects with the descriptions (leading to semantic insight vs. naive perception) had not yet taken place. On the other hand, the absence of reliable differences in Part I can be taken as evidence—with the usual caveats when interpreting null effects—that any subsequent effect of insight in Parts II and III cannot be explained solely by visual differences between the objects in the two conditions. Although the presentation of a matching or non-matching description for each object was counterbalanced across participants, the fact that different numbers of objects were excluded from the two conditions based on participants' self report in Part II would have made it possible for such visual differences to emerge as a confounding factor. If they did, however, one would expect to detect these differences even before any descriptions were presented, which we now know was not the case.

Effects of Insight in Part II

In Part II, half of the unfamiliar objects were presented with a matching verbal description (in the insight condition) and the other half were presented with a non-matching verbal description (in the naive condition). In response to objects for which participants experienced semantic insight, the amplitude of the N1 component was significantly enlarged (i.e. more negative), b = -0.64 µV, p = .026, and the amplitude of the N400 component was significantly reduced (i.e. less negative), b = 0.93 µV, p < .001, compared to objects which participants viewed naively. As in Part I, there were no reliable differences in the P1 component, p = .490.

Effects of Insight in Part III

In Part III, the unfamiliar objects were presented for a third time, again without the verbal descriptions (as in Part I), to test whether the occurrence of semantic insight had any lasting effects on the processing of the objects. As in Part II, the N400 component remained significantly reduced in response to objects for which semantic insight had occurred, b = 1.00 µV, p < .001, whereas the early effect of insight in the N1 component did not reoccur, p = .136. Instead, we now observed an even earlier modulation in the P1 component, which was significantly enlarged (i.e. more positive) in response to objects for which semantic insight had occurred, b = 0.55 µV, p = .031.

Discussion

In Experiment 1, we measured event-related brain potentials from participants viewing unfamiliar objects before (Part I), while (Part II) and after (Part III) they gained semantic insight into what kind of object they were seeing. To induce insight, half of the objects in Part II were preceded by a matching verbal description of the object's typical function or use, whereas the other half were preceded by a non-matching description (as a naive baseline condition).

Participants' experience of semantic insight in Part II was associated with a significantly enlarged N1 component, indicating that the sudden acquisition of knowledge about the object influenced aspects of its higher-level visual processing (Rossion & Jacques, 2011; Tanaka & Curran, 2001). The fact that this effect did not reoccur in Part III, when the objects were presented once more without descriptions, suggests it being a marker of semantic insight altering object processing online. In contrast, we also observed a modulation of the N400 component, which was reduced for objects when semantic insight was occurring (in Part II) and remained so when the same objects were presented repeatedly (in Part III). The N400 is most often discussed as an index of increased demands for semantic processing or integration (Kutas & Federmeier, 2011; Lau et al., 2008; Rabovsky et al., 2018). Its reduction can thus be interpreted as lowered semantic processing demands in response to unfamiliar objects once participants had understood what kind of object they were viewing. Finally, semantic insight was also associated with increased amplitudes in the P1 component, but only once the objects were presented for a third time (in Part III), after the critical presentation during which semantic insight had occurred (in Part II). This effect, which replicates previous work on obtaining knowledge about previously unfamiliar images (Samaha et al., 2018), may be associated with the newly acquired semantic knowledge exerting an influence on lower-level visual perception, either online or through altered visual representations of the objects for which insight had occurred.

Because of the exploratory nature of the present study and the novelty of the ERP effects observed in Experiment 1, we ran a replication study to assess the robustness of these findings in another samples of participants.

Experiment 2

Methods

Participants

Participants for Experiment 2 were 24 German native speakers (15 female, 9 male) with a mean age of 26 years (range 19 to 29) who had not participated in Experiment 1. They had no

Table 2

Results of linear mixed-effects regression models for Experiment 2

	P1		N1		N400	
Fixed effects	F (df)	p	F (df)	p	F (df)	p
Part	17.45 (2, 5267.1)	< .001	16.57 (2, 25.1)	< .001	70.12 (2, 25.2)	< .001
Insight	0.02 (1, 5276.9)	.900	0.98 (1, 5228.5)	.322	19.95 (1, 5242.5)	< .001
Pt. × ins.	3.60 (2, 5267.1)	.027	1.25 (2, 4756.5)	.287	7.92 (2, 4714.9)	< .001
Insight − naive	Est. [95% CI]	p	Est. [95% CI]	p	Est. [95% CI]	p
Part I	-0.16 [-0.71, 0.40]	.582	-0.03 [-0.53, 0.48]	.920	0.04 [-0.43, 0.50]	.877
Part II	-0.48 [-1.03, 0.08]	.094	-0.48 [-0.99, 0.03]	.064	1.33 [0.87, 1.79]	< .001
Part III	0.57 [0.01, 1.13]	.047	0.06 [-0.45, 0.57]	.818	0.47 [0.01, 0.93]	.047

Note. Pt. = part, ins. = insight, est. = estimate, CI = confidence interval.

history of psychological disorder or treatment, were right-handed and reported normal or corrected-to-normal vision. They gave written informed consent before starting the experiment and received a compensation of €8 per hour for participating.

Materials, Procedure, and Analysis

All materials, procedures, and methods for EEG recording and statistical analysis were identical to Experiment 1. An average of 5.8% of rare objects per participant was classified as known in Part I and excluded from all further analyses. Based on participants' responses in Part II, an average of 26.4 objects were assigned to the insight condition (44.0% of objects presented with a matching description) and an average of 49.2 objects were assigned to the naive condition (82.0% of objects presented with a non-matching description). Automatic rejection of EEG epochs containing artifacts led to the exclusion of 11.0 trials (3.0%) per participant (range 0 to 85).

Results

As in Experiment 1, P1, N1, and N400 amplitudes differed between the three different parts of the experiments, all Fs > 16.57, all ps < .001 (Table 2). Also as in Experiment 1, N400 amplitudes differed between the insight and the naive condition averaged across parts, F(1, 5242.5) = 19.95, $p < .001$. The part × insight interaction was significant in the P1 component, $F(2, 5267.1) = 3.60$, $p = .027$, and in the N400 component, $F(2, 4714.9) = 7.92$, $p < .001$, but not in the N1 component, $F(2, 4756.5) = 1.25$, $p = .287$.

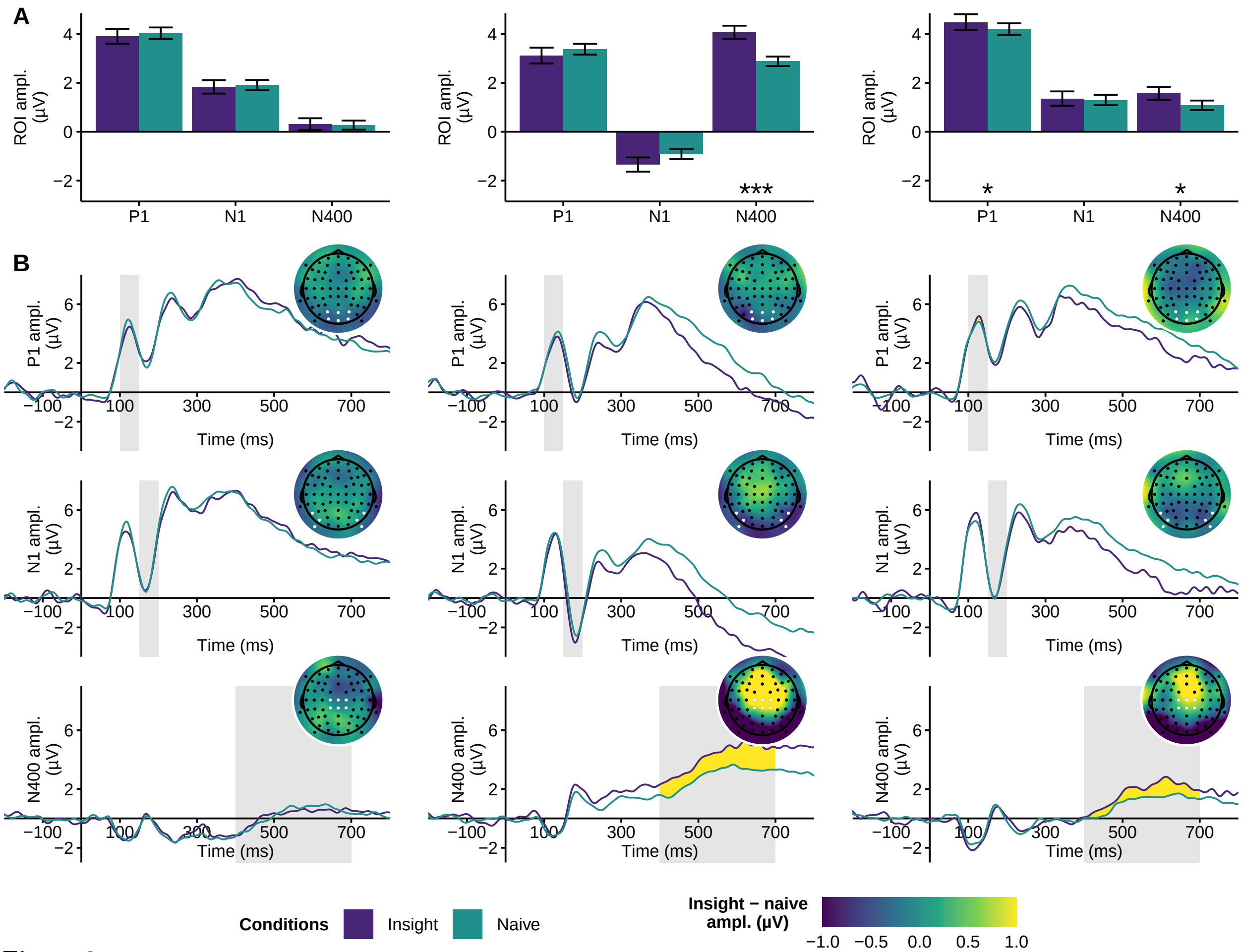

Figure 2

Results of Experiment 2. (A) Bar plots and (B) ERP waveforms and scalp topographies separately for objects for which participants experienced semantic insight and naive perception in Parts I, II, and III. In a direct replication of Experiment 1, the effect of semantic insight on the N400 component in Part II and on the P1 component in Part III remained statistically significant, while the effect on the N1 component in Part II and on the N400 component in Part III remained only marginally significant. Error bars show the standard error of the mean. Ampl. = amplitude.
$^*p < .05$. $^{***}p < .001$.

Effects of Insight in Part I

As in Experiment 1, no differences between objects in the insight and the naive condition emerged in the P1, N1, or N400 component, all ps $> .582$ (Table 2, Figure 2).

Effects of Insight in Part II

As in Experiment 1, the occurrence of semantic insight in Part II due to the presentation of objects with matching (vs. non-matching) verbal descriptions was associated with a (marginally) significant enhancement of the N1 component, b = -0.48 µV, p = .064, and a significant reduction of the N400 component, b = 0.93 µV, p < .001.

Effects of Insight in Part III

As in Experiment 1, the presentation of the same unfamiliar objects for a third time (without verbal descriptions as in Part I) led to significantly larger amplitudes in the P1 component in response to objects for which semantic insight had occurred, b = 0.57 µV, p = .047. Also, N400 amplitudes in response to these objects remained significantly reduced, b = 0.47 µV, p = .047.

Joint Analysis of Experiments 1 and 2

In an attempt to maximize statistical power, we combined the ERP data sets from Experiments 1 and 2. This allowed us to determine (a) if the above effects—including the marginally significant ones—were reliable when tested in a larger sample, and (b) if there were significant differences in the ERP amplitudes between Experiments 1 and 2. Methods for statistical analysis were kept unchanged apart from the addition of a new factor denoting the experiment, coded as a scaled sum contrast (i.e. subtracting Experiment 1 from Experiment 2, the intercept being the grand mean across both experiments; Schad et al., 2020). This factor and its possible interactions with part, insight, and part × insight were included in the linear mixed-effects regression models as fixed effects and as potential by-item random slopes. They were not included as by-participant random slopes since different participants took part in Experiments 1 and 2. Note that, as above, random effects were eventually included only if their omission led to a significant decline in model fit (Matuschek et al., 2017; Voeten, 2020).

As shown in Table 3, the main effect of the part of the experiment was significant in the P1, N1, and N400 component, all Fs > 12.38, all ps < .001, as was the main effect of insight in the N400, $F(1, 10518.8) = 38.72$, p < .001. Furthermore, the part × insight interaction was now

Table 3

Results of linear mixed-effects regression models for Experiments 1 and 2 combined

	P1		N1		N400	
Fixed effects	F (df)	p	F (df)	p	F (df)	p
Part	12.38 (2, 49.0)	< .001	29.90 (2, 50.0)	< .001	95.34 (2, 50.6)	< .001
Insight	0.35 (1, 10560.3)	.552	1.65 (1, 125.3)	.202	38.72 (1, 10518.8)	< .001
Experiment	0.35 (1, 48.2)	.555	2.38 (1, 48.1)	.129	4.75 (1, 48.4)	.034
Pt. × ins.	4.02 (2, 9042.4)	.018	5.60 (2, 9877.5)	.004	15.73 (2, 10010.1)	< .001
Pt. × exp.	0.03 (2, 49.0)	.971	0.55 (2, 50.0)	.581	2.58 (2, 50.6)	.085
Ins. × exp.	0.62 (1, 10536.2)	.432	0.04 (1, 10332.1)	.838	0.03 (1, 10574.9)	.865
Pt. × ins. × exp.	0.03 (2, 9042.9)	.972	0.62 (2, 9877.8)	.537	2.65 (2, 10010.4)	.070
Insight − naive	Est. [95% CI]	p	Est. [95% CI]	p	Est. [95% CI]	p
Part I	-0.07 [-0.44, 0.30]	.699	-0.10 [-0.44, 0.24]	.568	-0.10 [-0.41, 0.20]	.507
Part II	-0.22 [-0.59, 0.15]	.248	-0.56 [-0.90, -0.21]	.002	1.09 [0.79, 1.39]	< .001
Part III	0.49 [0.12, 0.86]	.010	0.25 [-0.10, 0.59]	.158	0.72 [0.41, 1.02]	< .001

Note. Pt. = part, ins. = insight, exp. = experiment, est. = estimate, CI = confidence interval.

observed reliably in all three components, all Fs > 4.02, all ps < .018. While there was a main effect of experiment in the N400, $F(1, 48.4) = 4.75$, $p = .034$, the absence of any significant interactions of experiment with part or insight indicated that the effects of our experimental manipulations did not differ between Experiments 1 and 2.

Based on the part × insight interaction, we again computed follow-up comparisons between the insight and the naive condition within each part, now collapsed across the data from both experiments. This confirmed the absence of any reliable differences between the two conditions in Part I, all ps > .507, the significant enhancement of the N1 component in Part II, while insight was occurring, b = -0.56 µV, p = .002, the significant reduction of the N400 component in Part II, while insight was occurring, b = 1.09 µV, p < .001, and Part III, after insight had occurred, b = 0.72 µV, p = < .001, as well as the significant enhancement of the P1 component in Part III, after insight had occurred, b = 0.49 µV, p = .010.

Control Analysis

One may raise concerns whether the modulation of the N1 component in Part II genuinely reflects semantic insight for objects in the respective condition, or—as an alternative explanation—whether it could be driven by the objects in the other, semantically naive condition. Remember that these objects were preceded by a non-matching description which was picked so that it could not be related to the object's visual features and their configuration. Thus, the modulation of the ERP components in Part II may reflect a mismatch response to those objects—reflecting, for example, the fact that the visual features of the object shown in Figure 1A cannot be reconciled with the function of morsing messages. To preclude this alternative explanation, we repeated the analysis above using a different baseline against which the objects in the insight condition were contrasted. Instead of the naive condition (where objects were presented with non-matching descriptions), we now used those objects which were preceded by matching descriptions (as in the insight condition), but which were excluded from the main analysis because participants indicated behaviorally that they did not understand the object they were seeing. Across both experiments, this was the case for 49.6% of objects presented with matching descriptions as compared to 44.4% of objects which did indeed lead to semantic insight (note that the remaining objects were excluded as not being unfamiliar in the beginning of the experiment). Just as above, this control analysis revealed a robust enhancement of the N1 component associated with semantic insight in Part II, b = -0.99 µV, $p < .001$. Thus, this enhanced negativity seems to be a genuine marker of semantically informed perception, no matter if compared to objects presented with misleading descriptions or compared to objects presented with accurate descriptions on which participants failed to capitalize. Note that the reduction of the N400 component also remained robust in this control analysis, b = 1.19 µV, $p < .001$.

Discussion

Experiment 2, which was a direct replication of Experiment 1, confirmed the impact of gaining semantic insight into previously unfamiliar objects on ERPs associated with lower-level visual perception (P1), higher-level visual perception (N1), and semantic processing (N400). While the enhancement of the N1 component, being more negative in response to objects for which participants were experiencing semantic insight, was present only during the critical presentation of the objects with their verbal descriptions (in Part II), the enhancement of the P1, being more positive in response to these same objects, emerged only after insight had taken place and the objects were presented again in Part III. This indicates a modulation of different stages of visual object perception through semantic knowledge, while and after an understanding of the object has been obtained. Finally, a sustained reduction of the N400 component in response to objects for which participants experienced semantic insight may reflect lowered semantic processing demands compared to unfamiliar objects which participants did not yet understand.

General Discussion

General discussion section goes here.

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