No matter how: Top-down effects of verbal and semantic category knowledge on early visual perception

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Published online: 3 January 2019
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Abstract

Language is assumed to augment human cognition. But can language also affect basic mechanisms of perception, suggesting cognitive penetrability of perception? This idea is highly controversial: linguistic categorization may induce top-down effects on ongoing perceptual processing. Alternatively, such effects may not concern perception proper, but pre-perceptual shifts of attention or downstream processes, such as perceptual judgment. This study provides a critical test of these views by investigating categorical perception (CP) of novel objects in a balanced learning design, controlling for perceptual experience and low-level visual differences. To better understand which linguistic representations induce CP, we manipulated the type of information categories were based on: bare verbal labels, in-depth semantic knowledge, or the combined information from labels associated with semantic knowledge. We used event-related brain potentials (ERPs) derived from the EEG in a visual search task to localize CP effects at perceptual or pre/post-perceptual stages. The results replicated behavioral CP with facilitated visual search when target and distractors belonged to different linguistic categories. ERPs revealed CP effects in the P1 and N1 components, associated with early visual processing. Attentional selection, reflected in the N2, also was influenced by linguistic categories. The N2 and the N400, a measure of high-level semantic processing, were sensitive to the depth of semantic knowledge associated with objects. CP, however, did not differ between category types, suggesting that any linguistic categorization can lead to CP. The findings support cognitive penetrability of perception, with linguistic categories informing perceptual predictions down to the processing of low-level visual features.

Keywords Categorical perception · Semantic knowledge · Event-related potentials · Linguistic relativity · Top-down effects

The Inuit are good at telling apart different kinds of snow, because they have an extraordinarily rich vocabulary for snow. Right? Wrong—but the persistence of this myth in folk psychology (Steckley, 2008) shows that there is something fascinating about the idea that language, categorization, and perception are somehow intertwined. Can language, a cognitive ability in its full manifestation unique to humans, affect our perceptual performance? Recent empirical evidence of the link between linguistic categorization and perception suggests

that it might. For instance, verbal labeling facilitates category learning and subsequent discrimination of visual (Lupyan, Rakison, & McClelland, 2007) and tactile stimuli (Miller, Schmidt, Blankenburg, & Pulvermüller, 2018). Evidence accumulates for language-based categorical perception effects (CP), that is, enhanced discrimination performance of stimuli from different linguistic categories compared with stimuli from the same category (Regier & Kay, 2009; Regier & Xu, 2017). CP has been shown for colors (Winawer et al., 2007; Witzel & Gegenfurtner, 2015, 2016) but similarly for faces (Yu, Li, Mo, & Mo, 2017) and objects (K. J. Holmes & Wolff, 2012). Some studies suggest that CP effects are stronger (or exclusively found) for stimuli presented in the right visual hemifield (RVF) compared with the left visual hemifield (LVF), implying a role of left-hemispheric language areas of the brain (Regier & Kay, 2009). However, this is not always the case (Witzel & Gegenfurtner, 2011, 2016; see *Discussion*). Interestingly, learning new linguistic categories also induces CP (Maier, Glage, Hohlfeld, & Abdel Rahman,

Electronic supplementary material The online version of this article (<https://doi.org/10.3758/s13415-018-00679-8>) contains supplementary material, which is available to authorized users.

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2014; Zhou et al., 2010), and concurrent verbal interference tasks cancel out CP (A. L. Gilbert, Regier, Kay, & Ivry, 2006; Roberson & Davidoff, 2000; Winawer et al., 2007). These observations suggest direct top-down influences of language on visual perception: linguistic categorization (e.g., calling two stimuli by the same or different names) may feed back to visual processing (Lupyan, 2012; Lupyan & Clark, 2015).

Controversy surrounding top-down effects on perception

The idea that linguistic categorization, or other cognitive factors, influence perception is facing theoretical and empirical challenges (Firestone & Scholl, 2015; Firestone & Scholl, 2016; Pylyshyn, 1999; Raftopoulos, 2015, 2017). There are starkly opposing views on cognitive penetrability of perception (Firestone & Scholl, 2016; Raftopoulos & Lupyan, 2018). In support of cognitive penetrability, it has been proposed that in CP, linguistic categories transiently warp perceptual space and tune ongoing perceptual processing to category-relevant stimulus features in a top-down fashion (Çukur, Nishimoto, Huth, & Gallant, 2013; Gilbert & Li, 2013; Lupyan, 2012; Lupyan & Clark, 2015). Opposing cognitive penetrability, it has been argued that early perceptual processing is encapsulated from cognition (Firestone & Scholl, 2016; Pylyshyn, 1999; Raftopoulos, 2015, 2017).

Avoiding experimental confounds

Conceiving of CP as genuine language-perception interaction faces certain empirical challenges. Effects should be clearly attributable to the top-down factor in question (i.e., linguistic categorization in the present study). Therefore, experimental designs must make sure to eliminate or control for low-level perceptual differences between conditions (Firestone & Scholl, 2015; Maier et al., 2014). Furthermore, effects should not be attributable to specific task demands or response biases (e.g., judging the steepness of a hill while wearing a heavy backpack in a research lab; Bhalla & Proffitt, 1999). One way to control this is making the manipulated factors task-irrelevant (Firestone & Scholl, 2016). Additionally, for CP to count as an effect of language, we believe that effects should not be related to explicit perceptual training on a specific category boundary (Goldstone, Lippa, & Shiffrin, 2001; Notman, Sowden, & Özgen, 2005; Özgen & Davies, 2002; Yu et al., 2017). While perceptual training studies of CP are clearly interesting in a different context, they cannot provide evidence for a role of language in CP.

Disentangling perception from other processing stages

The biggest challenge for evidence of top-down effects has to do with locating effects in actual perceptual processing (Firestone & Scholl, 2016; Pylyshyn, 1999; Raftopoulos, 2015, 2017). In the cognitive impenetrability view, although factors like linguistic categorization may enhance performance in visual perception tasks, effects could only be located pre- or post-perceptually but not within what is assumed to be early vision (Firestone & Scholl, 2016; Raftopoulos, 2015, 2017). Accordingly, cognitive factors would only have the potential to a) shift peripheral attention towards certain stimuli or features before actual perception starts, thus changing the input to perception and b) influence post-perceptual processing stages like judgments, memory, recognition, or response selection (Firestone & Scholl, 2016; Raftopoulos, 2015, 2017). Therefore, the timing question *when* cognitive factors influence processing in perception tasks is crucial. Neurocognitive methods, and especially electrophysiological measures with high temporal resolution, such as EEG and MEG, are well-suited to answer this question (Gazzaniga, Ivry, & Mangun, 2013). EEG has an excellent, millisecond-by-millisecond temporal resolution (Gazzaniga et al., 2013) and the functional significance of most visual event-related potential (ERP) components is well described (Kappenman & Luck, 2011; Luck, 2014).

Previous ERP studies have indeed shown effects of language on early visual processing, such as modulations of the P1 and N1 components (Boutonnet & Lupyan, 2015; Forder, He, & Franklin, 2017; Holmes, Franklin, Clifford, & Davies, 2009; Maier et al., 2014; Thierry, Athanasopoulos, Wiggett, Dering, & Kuipers, 2009). However, we are not sure that any of these studies can effectively rule out pre-perceptual shifts of attention (Raftopoulos, 2017), because they either employed pre-cueing paradigms (Boutonnet & Lupyan, 2015; Lupyan & Ward, 2013) or oddball tasks. In oddball tasks, stimulus categories can be chronically activated through the many repetitions of the same stimuli, which may cause shifts of pre-allocated feature based attention or set up stimulus expectancy (Forder, He, & Franklin, 2017; Holmes, Franklin, Clifford, & Davies, 2009; Maier et al., 2014; Thierry, Athanasopoulos, Wiggett, Dering, & Kuipers, 2009).

To address these points, we employed a learning design with object stimuli that were initially unknown to the participants. All participants saw all the objects—equally often—but learned to associate them with different linguistic and semantic information according to a counterbalanced study design (see *Design and Procedure*). Thus, perceptual learning was held constant and conditions differed solely in terms of linguistic category and semantic information. Low-level visual differences were eliminated by counterbalancing stimulus-condition-assignments across participants, effectively

excluding bottom-up differences between conditions. To preclude pre-perceptual shifts of attention and eliminate stimulus expectancy during perception, we employed a visual search task without verbal cues and with randomized (and therefore unpredictable) stimulus displays. Linguistic categories and semantic knowledge were task-irrelevant, precluding response biases and back-end memory or recognition effects (Firestone & Scholl, 2016). Crucially, we used ERPs to distinguish between perceptual and post-perceptual loci of CP effects.

Electrophysiological correlates of categorical perception

Previous studies, using oddball paradigms, reported CP effects as early as in the P1 component (Forder et al., 2017; A. Holmes et al., 2009; Maier et al., 2014; Thierry et al., 2009), an indicator of low-level visual processing, with generators in the extrastriate visual cortex (Clark, Fan, & Hillyard, 1994). One recent study found color CP in the P1 component to predict access to visual consciousness in the attentional blink paradigm (Maier & Abdel Rahman, 2018). Other studies found CP effects starting in the N1 time range (Boutonnet, Dering, Vinas-Guasch, & Thierry, 2013; Thierry et al., 2009; Yu et al., 2017), interpreted as a visual mismatch negativity, suggesting an effect of linguistic categories on preattentive perception (Thierry et al., 2009). In the context of visual object perception, the N1 is usually seen as an indicator of configural processing during early visual perception (Rossion & Jacques, 2011; Tanaka & Curran, 2001). However, it remains to be shown whether these CP effects on early visual processing are replicable without potential pre-perceptual shifts of attention. As discussed above, the argument that CP can be an instance of cognitive penetrability of perception hinges upon such evidence (Raftopoulos, 2017).

Categorical perception and the meaningfulness of categories

To date, little is known about precisely what types of linguistic representations lead to CP. One way to address this is to disentangle the contributions of verbal labels and their associated semantic content (Maier et al., 2014). Language can do much more than labeling categories. With language, we can effortlessly convey messages with nuanced semantic contents, and linguistic categories differ naturally in their meaningfulness. Research on semantic richness has shown that, for instance, English speakers name more semantic features associated with the word “bike” (e.g., “has two wheels”; “has brakes”; “is fast”) than with the word “tripod” (e.g., “has three legs”; “used by photographers”; McRae, Cree, Seidenberg, & McNorgan, 2005; Rabovsky, Sommer, & Abdel Rahman,

2012; Rabovsky, Schad, & Abdel Rahman, 2016). Visual perception, in turn, is not only influenced by categorization, but also by semantic knowledge. How much we know about an object’s function (e.g., objects that are used by farmers to breed eggs; Abdel Rahman & Sommer, 2008) or whether a combination of letters forms a meaningful word (Lupyan, 2017) influences visual perception. In this study, we investigated the role of meaningfulness of categories in CP.

We considered three scenarios for the relationship between verbal labels, semantic knowledge, and CP. First, it has been argued that verbal labels take on a special role in CP with a unique suitability to form and activate categorical representations (Boutonnet & Lupyan, 2015; Lupyan, 2012). For instance, priming visual perception with verbal labels (e.g., “cat”) works better than priming with semantically related cues (e.g., meowing; Boutonnet & Lupyan, 2015; Edmiston & Lupyan, 2015; Lupyan & Thompson-Schill, 2012). Accordingly, typical CP effects would be observed for categories learned with a singular, consistent label, but not (or to a lesser extent) for categories without a consistent category label. Second, the driving factor behind CP could be that there is a category at all, such that any information allowing categorization (e.g., a label or semantic knowledge) should lead to CP. This view is supported by one study suggesting that categories need not be labeled in order to induce CP and that it is sufficient to learn that two objects “go together” (Holmes & Wolff, 2012). Third, the depth of semantic knowledge associated with a linguistic category could influence CP. According to embodied approaches to linguistic representations, meaning is grounded in perception, action, and emotion (Barsalou 1999; Glenberg & Gallese, 2012). CP could result from the combined meaning of category labels and associated semantic knowledge (e.g., an object’s function or an animal’s prototypical sound), such that semantically richer, more palpable categories should lead to stronger CP. One previous study, however, does not suggest that more in-depth semantic knowledge associated with labels increases CP effects. Using ERPs and a visual oddball task, Maier et al. (2014) observed no difference in CP for novel object categories learned with both, labels and in-depth semantic knowledge and categories learned with labels only.

The present study

The present study’s first goal was to provide a critical test of CP as a top-down effect on perception. In a learning session, participants learned linguistic categories for novel, realistic objects. Later, they performed a visual search task established in previous studies investigating behavioral CP (Gilbert, et al., 2006; K. J. Holmes & Wolff, 2012) while EEG was recorded. By looking at ERPs and excluding cueing or priming effects, we disentangled early visual origins from pre- and post-

perceptual loci. We expected faster visual search for targets belonging to a different category than the distractors. Given the balanced learning design and the measures taken to prevent pre-perceptual shifts of attention, we would consider CP-effects in neural signatures of early visual processing as evidence of a genuine top-down effect on perception.

The second main goal was to better understand the linguistic representations that induce CP by investigating the roles of verbal labels and in-depth semantic knowledge. Three conditions were designed to distinguish between a potential label-advantage, CP based on any linguistic categorization, and CP resulting from labels associated with semantic knowledge. Object categories were formed based on labels only (labo), semantic knowledge only (semo), or labels + semantic knowledge (semlab; Fig. 1). CP effects observed in the labo and semlab conditions, but not the semo condition, would speak for the label-advantage hypothesis. Equal CP in all three conditions would mean that any categorization can lead to CP. If the strongest CP effects were observed in the semlab condition, this would suggest that CP results from the combined meaningfulness of linguistic category labels and associated semantic knowledge. Note that we consider all three types of categories to be linguistic and semantic: verbal labels bear (minimal) semantic knowledge (Abdel Rahman & Sommer, 2008), and in-depth semantic knowledge was transmitted verbally.

In line with previous findings, ERP analyses focused on the P1 and N1 components as indicators of ongoing visual processing, reflecting processing of low-level features (e.g., lightness or orientation contrast) and higher-level configural processing, respectively (Foxy & Simpson, 2002; Maier & Abdel Rahman, 2018; Maier et al., 2014; Scott, Tanaka, Sheinberg, & Curran, 2006). We took the N2 component as an indicator of attentional target selection (Folstein, Monfared, & Maravel, 2016; Folstein & Van Petten, 2008). If CP is reflected in early visual processing even in the absence of pre-cueing effects, CP should be observed already before the N2 component. We expected that CP should affect both, early perception (P1 and N1 component) and attention capture (N2 component).

Effects of CP on the P1—if reported at all—have been observed with different polarities. Using oddball tasks, Forder et al. (2017) found a reduced P1 for color deviants in the different category condition, whereas Maier et al. (2014) observed a P1 increase for deviant objects in the different category condition. Maier and Abdel Rahman (2018), investigating conscious detection in the attentional blink, also reported a P1 increase for targets containing a linguistically marked color contrast. Thus, while CP effects in the P1 are getting more established, the direction of effects is yet difficult to predict and likely to depend on stimulus and task properties (e.g., detection vs. discrimination; Van der Lubbe, Vogel, & Postma, 2005). We therefore had no specific prediction for the polarity of P1-effects in the setting of a visual search task.

Regarding the N1 component, we expected an increased (more negative) amplitude in the different category condition, in line with previous findings on the visual mismatch negativity (reviewed by Thierry, 2016). For the N2, we expected an increase (more negative amplitude) in the different category condition, reflecting facilitated attentional selection due to more salient search targets. To probe high-level semantic processing, we analyzed the amplitude of the N400 component, expecting an enhanced (more negative) N400 for objects learned with in-depth semantic knowledge (Abdel Rahman & Sommer, 2008).

Method

Participants

The final sample consisted of 30 native German speakers (16 women; mean age 23.3 years; age range 18–34). All were right-handed with normal or corrected-to-normal visual acuity. We predetermined inclusion criteria based on a recall questionnaire administered after the visual search task. Participants had to remember which objects belonged to the same category, for each object whether they had learned a name and/or in-depth knowledge, and a key phrase of the in-depth knowledge. Furthermore, only participants who did not make up names for objects to be learned without names or functions for objects in the labo condition were included. Four participants were excluded on this basis and replaced by others. No further participants had to be excluded on the basis of EEG data quality. The Ethics Committee of the Humboldt-Universität zu Berlin approved the study. Participants gave written, informed consent and received payment or course credits.

To determine the appropriate sample size, we ran a power analysis based on simulations with different sample sizes using the SIMR package in R (Green & MacLeod, 2016). We estimated the expected power to secure the fixed effect of category on P1-amplitude within the RVF based on the findings of Maier et al. (2014). The sample size had to be a multiple of six due to counterbalancing. Assuming an effect size of 0.4 μ V, 24 participants would be needed to achieve a power of 86.0% (95% confidence interval [CI]: 82.7, 88.9). We aimed for a larger sample size of 30 participants to increase statistical power to secure potential interaction effects with semantic knowledge, for which we had no priors.

Stimuli and apparatus

Object stimuli were grayscale photographs of 12 rare objects that were initially unknown to all participants with functions that could not be easily derived from the visual appearance. The stimuli were selected in such a way that groups of four objects were perceptually similar enough to be plausibly

Fig. 1 Learning Design (a) and Visual Search Task (b). Groups of four similar looking objects were categorized into pairs. Assignment of object pairs was counterbalanced across participants. For each group of objects,

categorization was based on one of the three types of semantic knowledge. In the visual search task, positions next to the vertical midline (upper two and bottom two positions) were not analyzed

grouped into one category but also distinct enough to be assigned to different categories, yielding three quadruplets of objects (see Fig. 1 for an example and Figure S1 of the Supplemental Material for all objects). In the visual search task, the objects were paired as follows: two pairs of same- and different-category objects were presented according to the information acquired in the learning session (Fig. 1). A third theoretically possible pair of different-category objects was not presented. This would have created a different number of trials for the same- and different-category conditions and thus may have created differences in implicit expectancy between conditions.

The size of the object pictures was $4.9^\circ \times 4.9^\circ$ visual angle in the learning session and $2.4^\circ \times 2.4^\circ$ in the test session. The visual search display consisted of 11 identical objects and one deviant, arranged in a circle (diameter = 9.34° at object picture centers). All stimuli were presented on a light blue background on a 19-inch monitor with a resolution of 1280×1024 pixels and a refresh rate of 75 Hz.

Object names were pseudowords consisting of three syllables (e.g., “PLONIDEX”). Every syllable appeared only in one object name. The names did not reveal meaningful information about functional properties. The objects to be learned without names were presented with random combinations of

seven consonants (e.g., “JRNKLSC”), with a new random combination each time. We recorded 6 spoken object descriptions to convey in-depth semantic knowledge, each explaining an object’s use and function (mean duration 24 s), and 16 stories containing object-unrelated information (cooking recipes; mean duration $M = 23.69$; see Fig. 1 for examples).

Design and Procedure

The study consisted of a learning session in which participants learned to categorize unfamiliar objects and a visual search experiment with EEG recording that took place 2 or 3 days later.

Learning session

Participants learned to categorize twelve objects into six pairs. Two object pairs were categorized together by sharing the same name (label only; labo condition), two pairs by sharing the same function (semantic knowledge only; semo condition), and two pairs by sharing the same name and function (label + semantic knowledge; semlab condition).

The learning session was an extension of the protocol reported in Maier et al. (2014) and lasted approximately 90 minutes. Only participants who were unfamiliar with all 12 object pictures started the learning session. The session consisted of three parts. Objects were always presented one at a time, together with the information to be learned (e.g., object name or audio description of the object function). In Part 1, participants learned the names of eight objects. The other four objects were presented with random letter combinations (semo condition). In Part 2, participants acquired in-depth semantic knowledge about eight of the objects (semo and semlab condition), describing object functions and use. For the other four objects, unrelated information (cooking recipes) was presented (labo condition). Cooking recipes were not repeated to avoid possible associations between objects and unrelated information. Presenting auditory input with all objects was meant to maximize procedural similarity between the knowledge conditions. In Part 3, participants further rehearsed the object names, as in Part 1. After Parts 1 and 3, speeded naming tests were conducted to check the learning progress. Fig. 1 illustrates the knowledge acquired during the learning session. For a more detailed description of the learning session’s protocol, including the timing of display presentations, we refer to the [Supplemental Material](#).

Test session

Participants performed a visual search task while the EEG was recorded. After a short practice block, participants performed 1,152 trials of the visual search task, organized in 4 blocks separated by self-paced breaks. Seven participants

accidentally performed a longer version of the task containing 1,728 trials in 6 blocks. We did not exclude these additional observations, because the linear mixed model (LMM) analyses we used are robust against unequal numbers of observations per cell (Pinheiro & Bates, 2000; cf. section “Statistical analyses”). The possible cognitive effects of longer task duration and an increasing number of stimulus repetitions should not differ between conditions.

Each trial started with the presentation of a fixation cross at the center of the screen, followed by the visual search display after 1 s, presented for 200 ms, then followed by a fixation cross that remained until a response was given or a maximum of 2.3 s. Participants indicated whether the deviant object was on the left or right side of the display by pressing a button with their right hand’s index (left) or middle finger (right). Within a search display, both objects were from the same quadruplet of visually similar objects. Trials ended with the response or after a timeout of 2 s. The order of trial presentation was fully randomized. After the visual search task, participants completed a debriefing questionnaire in which they recalled the information acquired in the learning session and answered questions about their experience with the experiment (e.g., difficulties with the task and presumed purpose of the study).

Design

The $2 \times 3 \times 2$ factorial design included the factors category (same, different), semantic knowledge (labo, semo, semlab), and visual field (left = LVF, right = RVF). Category and semantic knowledge conditions were fully counterbalanced across participants such that each object appeared equally often in each condition and the same visual search displays were shown in each condition.

Statistical analyses

Statistical analyses were performed with R (version 3.4.2., R Core Team, 2017). To only analyze visual search displays with targets clearly lateralized to one visual field, we excluded trials in which the target was shown in one of the four positions closest to the vertical midline (i.e. next to 12 o’clock or 6 o’clock) from all analyses. In the analysis of response times (RTs) and ERPs, we only considered trials with correct responses. RTs were corrected for outliers by excluding RTs faster than 150 ms and RTs exceeding each individual participant’s mean RT by 3 *SD*. RTs were then log-transformed to achieve a normal distribution and subjected to linear mixed models (LMMs) using the lme4 package (Bates, Mächler, Bolker, & Walker, 2014). *P* values were computed with the lmerTest package (Kuznetsova, Brockhoff, & Christensen, 2016), using Satterthwaite approximation for degrees of freedom.

We tested for effects of the fixed factors category, knowledge, and visual field on behavioral measures (visual search accuracy and RT) and ERP-amplitudes. For all fixed factors, we applied sliding difference contrasts, such that the resulting estimates can be directly interpreted as the difference between adjacent factor levels (e.g., same minus different category). We used the nesting functionality of the lme4 package to compute pairwise comparisons between factor levels of category and semantic knowledge nested within visual field (e.g., same vs. different category for targets in the right visual field). Nested models in lme4 are equivalent to nonnested models in terms of model fit indices.

We modeled random intercepts for participants (e.g., variance in average RT or ERP amplitude across participants) and object pairs, as well as random slopes for the fixed factors (estimates of variance in the effect of a given manipulation across individuals or items). The inclusion of random intercepts for object pairs aimed to reduce the dependency of effects on our particular stimulus set. Random effects not supported by the data, that is, explaining zero variance according to singular value decomposition, were excluded to prevent overparameterization (Matuschek, Kliegl, Vasishth, Baayen, & Bates, 2017).

Fixed-effects structures of LMMs were reduced stepwise by excluding nonsignificant interaction terms/fixed factors and compared using the anova function until the respectively smaller model explained the data significantly worse than the larger model (significant χ^2 test). We further compared and report AIC (Akaike Information Criterion) and BIC (Bayesian Information Criterion), fit indices that are smaller for better fitting models. Data and analysis scripts are available at the Open Science Framework (osf.io/zhdr3).

EEG recording and analysis

The EEG was recorded with sintered Ag/AgCl electrodes at 64 scalp sites according to the extended 10–20 system. The sampling rate was 500 Hz. During recording, low- and high-cutoff filters (0.032 Hz and 1,000 Hz) were applied and all electrodes were referenced to the left mastoid. Electrode impedance was kept below 5 k Ω . Electrooculograms were recorded from electrodes F9 and F10 (horizontal EOG) and electrodes IOL and FP1 (vertical EOG). After the visual search task, participants made prototypical eye movements in a calibration procedure for later artifact correction. Offline processing steps were made in MATLAB 2016a using functions of the EEGLAB toolbox (Delorme & Makeig, 2004) in an analysis pipeline described in detail for a different dataset (Frömer, Maier, & Abdel Rahman, 2018), available from the Open Science Framework (osf.io/hdxvb). After re-referencing the continuous EEG to a common average reference, eye movement artifacts were removed with a spatio-temporal dipole modeling procedure using the BESA software (Ille, Berg,

& Scherg, 2002). Remaining artifacts were eliminated with an automatic artifact rejection procedure (amplitudes exceeding ± 200 μ V or changing by more than 50 μ V between two successive samples or by 200 μ V within intervals of 200 ms). Artifact-free data were segmented into epochs of 1 s, time-locked to the onset of the visual search display, including a 200-ms pre-stimulus baseline interval. ERPs were low-pass filtered at 40 Hz and baseline-corrected using the 200-ms time-window before stimulus onset. Single-trial ERPs were averaged across the time windows of interest corresponding to the P1, N1, N2, and N400 components. P1 amplitude was quantified as the mean amplitude at electrodes O1, O2, PO3, PO4, PO7, and PO8 between 80 and 110 ms (Pratt, 2011). For the N1, we used the same electrodes between 140 and 180 ms (Pratt, 2011). For the N2, we used electrodes O1, O2, PO3, PO4, PO7, PO8, P5, P6, P7, and P8 between 240 and 290 ms (Luck, 2011). For the N400, we used electrodes Cz, C1, C2, FC1, FC2, FC3, and FC4 between 500 and 600 ms (Kutas & Federmeier, 2011). These single trial mean amplitudes were subjected to LMMs as described in the previous section.

Results

Behavioral results

Mean accuracy in the visual search task was $M = 94.7\%$ (95% CI $\pm 0.3\%$). Mixed-effects logistic regression yielded no effects of visual field ($b = 0.17$, $z = 1.18$, $p = 0.238$), category ($b = 0.05$, $z = 0.82$, $p = 0.415$), or semantic knowledge (semo-labo: $b = -0.06$, $z = -0.87$, $p = 0.385$; semlab-semo: $b = 0.01$, $z = 0.15$, $p = 0.882$) on accuracy.

Mean RTs were shorter in the different category ($M = 460.8$ ms, CI ± 2.3 ms) compared with the same category condition ($M = 462.6$ ms, CI ± 2.3 ms). Model estimates of the LMM analysis of log-transformed RTs are summarized in Table 1. In line with the assumption of CP, there was a significant main effect of category. Furthermore, RTs were significantly shorter for RVF targets than LVF targets. There were no significant interactions of category and visual field or category and semantic knowledge, but a significant three-way interaction (Fig. 2). A follow-up analysis with the same model, but category nested within semantic knowledge and visual field, showed a significant CP effect in the LVF in the semlab condition ($b = -0.01$, $t = -2.17$, $p = 0.030$), as well as a trend in the RVF in the labo condition ($b = -0.01$, $t = -1.95$, $p = 0.051$).

Given evidence that CP effects may differ between fast and slow responses (Constable & Becker, 2017; Witzel & Gegenfurtner, 2016), we tested whether the CP effect was distributed evenly across slow and fast RTs by splitting mean RTs into quartiles according to each individual participant's distribution of RTs (Fig. 2). Post-hoc analysis of log-

Table 1. Effects of visual field, semantic knowledge and category on log-transformed RT

Variable	Estimate	SE	<i>t</i> -value	<i>p</i> value
Intercept	6.122	0.022	281.94	<0.001***
Visual Field(R-L)	-0.017	0.008	-2.23	0.029*
Sem(Semo-Labo)	0.004	0.004	0.86	0.397
Sem(Semlab-Semo)	-0.004	0.005	-0.70	0.492
Category(D-S)	-0.004	0.002	-1.99	0.047*
Visual Field:Sem(Semo-Labo)	0.008	0.005	1.45	0.146
Visual Field:Sem(Semlab-Semo)	-0.003	0.005	-0.55	0.585
Visual Field:Category	-0.001	0.004	-0.25	0.801
Sem(Semo-Labo):Category	0.005	0.005	0.92	0.357
Sem(Semlab-Semo):Category	-0.002	0.005	-0.42	0.678
Visual Field:Sem(Semo-Labo):Category	-0.004	0.011	-0.41	0.684
Visual Field:Sem(Semlab-Semo):Category	0.026	0.011	2.46	0.014*
Variance components	SD	Goodness of fit		
Participants (Intercept)	0.09	Log likelihood		8753.9
Visual Field	0.04	REML deviance		-17507.8
Object Pair (Intercept)	0.07			
Sem(Semo-Labo)	0.02			
Sem(Semlab-Semo)	0.02			
Visual Field	0.01			
Residual	0.17			

Note: R-L = RVF-LVF, D-S = Different Category-Same Category, Sem = Semantic Knowledge.

“.” indicates interactions between fixed factors. *** $p < 0.001$, * $p < 0.05$

transformed RTs with the factor category nested within quartiles yielded a significant CP effect only in the slowest quartile of RTs. The model estimates are summarized in Table 2.

EEG results

P1 component

Topographies of the P1 component for targets in the LVF and RVF suggested that the P1 was asymmetric as a function of visual field (Clark et al., 1994). Notably, the P1 seemed reduced for the RVF at ipsilateral electrodes (Fig. 3). We therefore tested for differences between P1 amplitudes in the LVF

and RVF using cluster-based permutation statistics (CBPT) as implemented in FieldTrip (Oostenveld, Fries, Maris, & Schoffelen, 2011). This method allows analyzing ERPs over all channels without pre-specifying a region of interest, while effectively controlling for multiple comparisons. For a more detailed description, please see Maris and Oostenveld (2007) and Frömer, Maier, and Abdel Rahman (2018). Confirming the visual impression, P1 amplitude was significantly reduced for RVF targets at right-hemispheric electrodes. Fig. 3 shows raw P1-topographies separately for the LVF and RVF, as well as a difference topography with electrodes underlying the significant difference between both conditions marked as dots. Based on this result, we refined the ROI analysis by

Fig. 2 Effect of Category on RTs, separated by Visual Field and Semantic Knowledge (left panel) and by Quartiles of RT (right panel). Error bars represent 95% CI

Table 2 Effects of category by quartiles of RT

Variable	Estimate	SE	<i>t</i> -value	<i>p</i> value
Intercept	5.93	0.017	344.66	<0.001***
Q1/Category(D-S)	-0.001	0.002	-0.44	0.663
Q2/Category(D-S)	-0.001	0.002	-0.34	0.735
Q3/Category(D-S)	-0.001	0.002	-0.34	0.736
Q4/Category(D-S)	-0.006	0.002	-2.91	0.004**
Variance components	SD	Goodness of fit		
Participants (Intercept)	0.09	Log likelihood	29546.7	
Object Pair (Intercept)	0.01	REML deviance	-59093.4	
Residual	0.07			

Note: Q1–4 = Quartiles 1–4, D-S = Different Category–Same Category
 “/” indicates nesting of fixed factors. *** $p < 0.001$, ** $p < 0.01$

aggregating the P1 at contralateral ROI electrodes, i.e., electrodes O1, PO3, and PO7 for RVF targets and O2, PO4, and PO8 for LVF targets.

We then computed separate LMMs for each ROI with category nested within visual field. P1-amplitude in the left-hemispheric ROI was reduced for different-category targets compared with same-category targets in the RVF ($b = -0.25$, $t = -1.99$, $p = 0.046$) but not the LVF ($b = -0.03$, $t = -0.23$, $p = 0.821$). Analysis of the right-hemispheric ROI yielded no significant category effect (LVF: $b = -0.18$, $t = -1.35$, $p = 0.177$; RVF: $b = -0.02$, $t = -0.15$, $p = 0.883$). Fig. 4 illustrates ERPs and difference topographies for these comparisons. There were no effects of semantic knowledge and excluding this fixed factor did not decrease but increased the model fit ($\Delta_{AIC} = -4$, $\Delta_{BIC} = -20$ in both ROI models).

N1 component

Analysis of N1 amplitudes revealed three-way interactions of visual field $\times$ semantic knowledge (semo–labo) $\times$ category ($b = 0.74$, $t = 2.00$, $p = .045$), as well as visual field $\times$ semantic knowledge (semlab–semo) $\times$ category ($b = -0.78$, $t = -2.09$, $p = 0.037$). We followed this up by running the model again with category and semantic knowledge nested within visual

field. The estimates of the nested model are summarized in Table 3. This analysis revealed a category effect in the RVF, independent of semantic knowledge, with a larger (more negative) N1 in the different category compared with the same category condition. In addition, there was an interaction of category $\times$ semantic knowledge (semlab–semo) in the LVF. As shown in Fig. 4, within the LVF, the semo condition yielded a pattern comparable to the CP effect observed in the RVF, with a numerically larger N1 for different category targets compared with same category targets ($b = -0.32$, $t = -1.74$, $p = 0.082$). In the semlab condition, this pattern was reversed ($b = 0.25$, $t = 1.35$, $p = 0.178$). Note that, despite the interaction, the individual comparisons in the nested model were not significant.

N2 component

The N2 component, an indicator of attentional target selection, was larger (more negative) in the different category compared with the same category condition. Additionally, the N2 scaled with semantic knowledge (Fig. 5). LMM analysis revealed main effects of category, semantic knowledge (semo–labo and semlab–semo), as well as visual field. Model estimates are summarized in Table 4. There were no interactions and excluding the interaction terms did not significantly reduce but improved the model fit ($\Delta_{AIC} = -8$, $\Delta_{BIC} = -64$).

N400 component

The N400 scaled with semantic knowledge. N400 amplitude was most negative in the semo condition and most positive in the labo condition, with the semlab condition in between (Fig. 5). LMM analysis yielded a significant difference between the semo and the labo condition ($b = -0.22$, $t = -2.92$, $p = 0.003$) and no difference between the semlab and the semo condition ($b = 0.12$, $t = 1.64$, $p = 0.100$). Model selection favored the reduced model with semantic knowledge as the only fixed factor over the full model ($\Delta_{AIC} = -6$, $\Delta_{BIC} = -29$).

Fig. 3 Topographical maps of the P1 component by Visual Field, averaged between 80–110 ms after stimulus onset. The left and middle panel show the raw P1 topographies for the LVF and RVF, respectively. The right panel depicts the difference topography (RVF–LVF).

Highlighted electrodes are part of the spatio-temporal cluster underlying the significant difference between P1 components in the LVF versus RVF. The P1 was asymmetric, yielding significantly reduced amplitude at right-hemispheric electrode sites for RVF targets

Fig. 4 CP effects in the P1 and N1 components separately for the LVF (left panel) and RVF (right panel). There were no significant CP effects in either component in the LVF (left panel), but an interaction between Category and Semantic Knowledge (Semlab-Semo, bottom topographies). In the RVF, there were CP-effects in both, the P1 and N1

component. Analyzed time windows are highlighted in gray in the ERP-curves. Topographies show mean differences between conditions in the time windows of the P1 and N1 components. ROI-electrodes are highlighted as dots

Table 3 N1 component: effects of category and semantic knowledge nested within visual field

Variable	Estimate	SE	<i>t</i> -value	<i>p</i> value
Intercept	-4.90	0.94	-5.20	<0.001***
Visual Field(R-L)	-0.01	0.08	-0.15	0.878
Sem(Semo-Labo)	0.05	0.09	0.49	0.626
Sem(Semlab-Semo)	-0.07	0.09	-0.77	0.443
LVF/Category(D-S)	<0.01	0.11	0.06	0.956
RVF/Category(D-S)	-0.24	0.11	-2.23	0.026*
Visual Field:Sem(Semo-Labo)	0.04	0.19	0.24	0.815
Visual Field:Sem(Semo-Labo)	0.03	0.19	0.15	0.885
LVF/Category:Sem(Semo-Labo)	-0.42	0.26	-1.58	0.114
RVF/Category:Sem(Semo-Labo)	0.33	0.26	1.25	0.213
LVF/Category:Sem(Semlab-Semo)	0.58	0.26	2.18	0.029*
RVF/Category:Sem(Semlab-Semo)	-0.20	0.26	-0.77	0.442
Variance components	SD	Goodness of fit		
Participants (Intercept)	5.13	Log likelihood		-71393.4
Visual Field	0.12	REML deviance		142786.8
Object Pair (Intercept)	0.40			
Residual	5.69			

Note: R-L = RVF-LVF, D-S = Different Category-Same Category, Sem = Semantic Knowledge

“:” indicates interactions between fixed factors, “/” indicates nesting of fixed factors. *** $p < 0.001$, * $p < 0.05$

Fig. 5 Effects of Semantic Knowledge on the N2 (left panel) and N400 component (right panel). In the N2, both comparisons showed significant differences, in the N400, the Semo and Labo conditions differed significantly. Analyzed time windows are highlighted in gray in the

ERP-curves. Topographies show mean differences between conditions in the time windows of the N2 and N400 components. ROI-electrodes are highlighted as dots

ERP components as predictors for RTs

We ran a post-hoc analysis to investigate whether neural signatures of early visual processing (P1 and N1 component of the ERP) and attentional selection (N2 component) were related to the categorical perception effect observed in visual search performance. To this end, we included single-trial amplitudes of the P1, N1, and N2 components, as well as the fixed factor category as predictors in a linear mixed model

Table 4 N2 component: effects of visual field, category, and semantic knowledge

Variable	Estimate	SE	<i>t</i> -value	<i>p</i> value
Intercept	4.68	0.65	7.21	<0.001***
Visual Field(R-L)	-0.35	0.13	-2.64	0.013*
Category(D-S)	-0.14	0.06	-2.21	0.027*
Sem(Semo-Labo)	0.38	0.12	3.20	0.003**
Sem(Semlab-Semo)	-0.60	0.16	-3.71	<0.001***
Variance components	SD	Goodness of fit		
Participants (Intercept)	3.48	Log likelihood	-67402.0	
Visual Field	0.63	REML deviance	134804.0	
Sem(Semo-Labo)	0.50			
Sem(Semlab-Semo)	0.77			
Object Pair (Intercept)	0.60			
Residual	4.75			

Note: R-L = RVF-LVF, D-S = Different Category-Same Category, Sem = Semantic Knowledge

****p* < 0.001, ***p* < 0.01, **p* < 0.05

analysis of log-transformed RTs. Because the P1 component was averaged separately for the left and right visual field, we ran two LMM analyses—one for each visual field. Tables 5 and 6 summarize the results for the LVF and the RVF, respectively. Both analyses revealed a main effect of the N2 component on RTs, with larger (more negative) N2 amplitudes associated with longer reaction times. Neither the P1 nor the N1 component was predictive of RTs.

Table 5 Effects of P1, N1, N2, and category on log-transformed RT in LVF trials

Variable	<i>b</i>	<i>SE</i>	<i>t</i> -value	<i>p</i> value
Intercept	6.129	0.023	269.52	<0.001***
P1 amp	-0.003	0.002	-1.38	0.168
N1 amp	-0.005	0.003	-1.78	0.075
N2 amp	-0.009	0.004	-2.36	0.018*
Category(D-S)	-0.005	0.004	-1.13	0.271
P1 amp:Category	-0.003	0.004	-0.67	0.502
N1 amp:Category	-0.003	0.004	0.70	0.483
N2 amp:Category	-0.004	0.006	-0.76	0.445
Variance components	SD	Goodness of fit		
Participants (Intercept)	0.09	Log likelihood	4447.7	
Object Pair (Intercept)	0.08	REML deviance	-8895.4	
Category	0.02			
Residual	0.16			

Note: amp = scaled and centered mean amplitude, D-S = Different Category-Same Category

“:” indicates interactions between fixed factors. ****p* < 0.001, **p* < 0.05

Table 6 Effects of P1, N1, N2, and category on log-transformed RT in RVF trials

Variable	<i>b</i>	<i>SE</i>	<i>t</i> -value	<i>p</i> value
Intercept	6.111	0.020	298.53	<0.001***
P1 amp	-0.001	-0.002	-0.44	0.658
N1 amp	-0.004	-0.003	-1.12	0.263
N2 amp	-0.015	-0.004	-3.97	<0.001***
Category(D-S)	-0.003	-0.004	-0.82	0.421
P1 amp:Category	-0.003	-0.005	0.61	0.543
N1 amp:Category	-0.004	-0.005	-0.95	0.344
N2 amp:Category	-0.002	-0.006	0.34	0.738
Variance components	<i>SD</i>	Goodness of fit		
Participants (Intercept)	0.08	Log likelihood	3931.5	
Object Pair (Intercept)	0.07	REML deviance	-7863.1	
Category	0.01			
Residual	0.17			

Note: amp = scaled and centered mean amplitude, D-S = Different Category-Same Category

“:” indicates interactions between fixed factors. *** $p < 0.001$

Discussion

This study investigated the effect of learning linguistic categories for novel, unfamiliar objects on perceptual processing during discrimination of these objects in a visual search task. Two questions were in the main focus: First, do linguistic categories have a top-down influence on early perceptual processing? Second, what types of linguistic representations lead to CP? Are labeled categories special, does meaningfulness enhance CP effects, or does any linguistic categorization induce CP?

Regarding the first research question, our study design addressed important challenges associated with the study of top-down effects (Firestone & Scholl, 2016; Pylyshyn, 1999; Raftopoulos, 2015, 2017). By asking participants to learn linguistic categories for novel objects in a strictly balanced learning protocol, we controlled for perceptual experience, making sure that effects are indeed related to learned linguistic and semantic knowledge. The learning design ensured that the same objects were presented equally often in all experimental conditions, eliminating bottom-up visual differences (Firestone & Scholl, 2015). Visual discrimination of objects was tested with a visual search task for which the previously learned information was irrelevant, ruling out post-perceptual effects like judgments or response bias (Firestone & Scholl, 2016). Presentation of visual search displays in random order and without cues prevented explicit or implicit preparatory activation prior to the stimulus displays. Therefore, changes to perception could not be induced by pre-perceptual shifts of attention (Firestone & Scholl, 2016; Raftopoulos, 2017). Finally, we capitalized on the high temporal resolution of

ERPs to disentangle modulations of early perceptual processing from downstream processing stages, such as attention capture or response selection. With these precautions, we assumed that any remaining effect of linguistic categorization or semantic knowledge on early visual processing, as reflected in well-established ERP components P1 and N1, would constitute evidence in favor of true top-down effects. Indeed, we found evidence of CP in visual search performance, as well as the P1 and N1 components. CP was also evident at the later stage of attentional selection reflected in the N2 component.

Regarding the second research question, novel object categories were learned with bare verbal labels, with semantic knowledge only, or with labels and semantic knowledge combined. Main effects of category in behavior and ERPs showed that CP did not differ between the three types of categories. This suggests that any linguistic categorization can induce CP (see discussion below).

Behavioral categorical perception effect

The results replicate and significantly extend previous findings on linguistically induced CP. In line with a behavioral CP effect, visual search was faster when the target belonged to a different category than the distractors, compared with targets belonging to the same category (Goldstone & Hendrickson, 2010). As in the study by Witzel and Gegenfurtner (2016), reanalysis of RTs by quartiles showed that CP was only present in slow reactions (i.e., more difficult search displays), independent of the visual field.

The finding of behavioral CP is a significant addition to previous electrophysiological findings obtained with oddball tasks that were less suitable to investigate behavioral CP (Forder et al., 2017; A. Holmes et al., 2009; Maier et al., 2014; Thierry et al., 2009). Even though the effect as such is numerically small, this result is relevant, because it helps to bridge the gap between the behavioral benefit associated with CP and electrophysiological signatures found in the present and several previous studies (Boutonnet et al., 2013; Forder et al., 2017; Holmes et al., 2009; Mo, Xu, Kay, & Tan, 2011; Thierry, 2016; Thierry et al., 2009), by showing behavioral and ERP effects in the same task.

Categorical perception effects in ERP components

The earliest onset of CP was observed in the P1 component and was statistically significant only for targets in the RVF. The CP effect specifically on the P1, traditionally associated with processing of low-level visual features, such as luminance and stimulus size, as well as pre-allocated spatial attention (Mangun & Hillyard, 1991), adds to previous evidence that CP involves modulations of early visual processing (Forder et al., 2017; Holmes et al., 2009; Maier et al., 2014; Maier & Abdel Rahman, 2018; Thierry et al., 2009). Here, the

novel demonstration that CP is reflected in early visual processing even when stimulus categories are unpredictable and there are no verbal cues adds an important point to the debate on top-down effects. As a point of caution, it should be noted that the CP effect in the P1 was only observed at contralateral electrodes. Although not predicted, this fits the observed asymmetry of the P1 component (Fig. 3) and can be explained with the lateralized presentation of targets in the visual search task (Clark et al., 1994).

The N1, thought to reflect configural visual processing, most notably during face perception (Rossion & Jacques, 2011), revealed a clear pattern of CP lateralized to the RVF. This effect might be a continuation of the CP effect beginning in the P1 or constitute an own stage in the time course of CP. In line with previous findings on the visual mismatch negativity (reviewed by Thierry, 2016), the N1 effect could reflect perceived homogeneity of the search display, with displays containing a target from a different category eliciting a greater mismatch response. This suggests that the N1 reflects a more salient visual pop-out in the different category condition.

As expected, a category effect was also observed in post-perceptual processing, namely with a larger N2 component for different category targets. This effect was nonlateralized. In visual search, the N2 is thought to reflect attentional selection of targets (Folstein et al., 2016; Luck, 2011). So, mirroring behavioral results, the N2 revealed facilitation of the attentional selection of putatively more salient targets in the different category condition (Maier & Abdel Rahman, 2018).

An additional analysis tested the relationship between the P1, N1, and N2 components and the behavioral CP effect. This analysis yielded a main effect of the N2 component on RTs, but no interaction effects between ERPs and category, suggesting that no single component underlay behavioral CP. Thus, although learning novel linguistic categories clearly entails modulations of early visual processing, this does not necessarily transfer into the aggregate measure that is reaction time. The lack of an interaction between ERP amplitudes and category could also be due to the overall small categorical perception effect in RTs, leaving little variance for ERPs to explain. Alternatively, the early modulations associated with categorical perception may still be related to visual search performance, but in a more complex manner than can be grasped with single trial linear regression.

Even though in the present data, the modulations of early visual processing did not directly predict differences in performance, they add to a better understanding of categorical perception, because “any information represented in the brain holds the potential to influence behavior” (Harris, McMahon, & Woldorff, 2013). The relationship between neural markers and behavior may crucially depend on the kind and the difficulty of perceptual tasks (Regier & Xu, 2017). For instance, using the same type of LMM analysis, Maier & Abdel Rahman (2018) observed a relationship between a categorical

perception effect in the P1 component and subsequent conscious perception of targets in a difficult attentional blink task.

Polarity of P1 effects

CP clearly affected early visual processing, which is interesting in itself, but the exact mechanism remains to be better understood. Here, P1 amplitude was reduced in the different category condition compared to the same category condition. Previous studies, in contrast, found a P1 increase for targets in the different category condition, related to conscious detection in the attentional blink paradigm (Maier & Abdel Rahman, 2018) and processing of deviants in an oddball paradigm using novel objects similar to the present study (Maier et al., 2014). In these studies, the larger P1 was assumed to reflect increased visual saliency of targets crossing a linguistic category boundary. This saliency increase interpretation matches findings of enhanced P1 amplitudes observed for targets primed with spatial attention cues (Mangun & Hillyard, 1991; Luck, Woodman & Vogel, 2000) and verbal labels (Boutonnet & Lupyan, 2015), both related to facilitated target processing. Yet again, matching the present P1 effect, a recent study also showed CP as a P1 reduction in an oddball paradigm with color stimuli (Forder et al., 2017). The polarity of such subtle P1 effects may vary between different tasks, such as discrimination versus detection (Van der Lubbe et al., 2005), attended versus unattended deviants (Forder et al., 2017; Maier et al., 2014), and stimuli used (e.g., color contrasts vs. complex objects; Forder et al.; Maier et al., 2014). Another possibility discussed by Forder et al. (2017), that would fit the present result, is that a P1 reduction in the different category condition reflects an early onset of the mismatch negativity typically observed in the subsequent N1 time range (reviewed by Thierry, 2016).

Main effects of visual field

We observed main effects of visual field in RTs and the N2 component, suggesting attentional bias to RVF targets. There are two explanations for this observation that have to do with the fact that all participants were right-handed and used the right hand to respond. First, it could be a simple stimulus-response compatibility advantage for RVF targets (Fitts & Seeger, 1953). Second, the response buttons were not positioned centrally but closer to the right side of the monitor. Perceptual performance can be improved for the space proximal to an effector, and effects are stronger for the dominant hand (Le Bigot & Grosjean, 2012). One explanation for this is increased deployment of attention towards the space around the response hand (Le Bigot & Grosjean, 2012). This also would be in line with the observed asymmetric topography of the P1 component (Fig. 3). In any case, an RVF advantage should not differentially affect the category and semantic

knowledge conditions. However, it is conceivable that a default bias to direct attention to the RVF might influence lateralization of early CP by delaying processing of targets in the LVF and preventing an early influence of category or semantic knowledge in the LVF. Future research could address this question by directly manipulating pre-allocated spatial attention.

Lateralization of categorical perception

In RTs, there was no interaction of category and visual field, suggesting that the visual discrimination benefit was not stronger in (or exclusive to) targets in the RVF, in contrast with some previous findings (Drivonikou et al., 2007; Franklin et al., 2008; Gilbert et al., 2006; Roberson, Pak, & Hanley, 2008; Zhou et al., 2010) but in line with others (Witzel & Gegenfurtner, 2011, 2015, 2016). Roberson et al. (2008) found lateralization of CP to the RVF only in fast responders (Constable & Becker, 2017). However, “fast” reactions in previous studies were still relatively slow compared with the present study, suggesting that the visual search task used here was generally easier and more susceptible to bottom-up visual pop-out, and the average category-advantage was small compared to other studies. Thus, occurrence and lateralization of the behavioral CP effect appear to be task-dependent (Regier & Xu, 2017). We assume that visual discrimination needs to be difficult enough for categorical enhancement of visual saliency at a low perceptual level to be behaviorally relevant (mean RTs around 600 ms; Constable & Becker, 2017). Given this premise, relatively faster reactions may then exhibit lateralization of CP to the RVF. In line with this idea, CP in the P1 and N1 components was restricted to targets in the RVF. This suggests that early, automatic visual processing is more susceptible to the influence of linguistic categories in the language-dominant left hemisphere of the brain (Regier & Kay, 2009).

While early perceptual ERP components revealed a pattern of lateralized CP in the RVF, attentional selection (N2 component) was category-sensitive but showed no lateralization. The CP effect in RTs also was not lateralized. Taken together, while CP is clearly reflected in neural signatures of early visual perception, the pattern of this early signal does not necessarily transfer to reaction times. We argue that this depends on task difficulty: in perceptually difficult tasks, CP signatures in the P1 or N1 should be more likely to make a difference for behavior and carry on lateralized CP. Here, the visual search task was rather easy compared with other studies (Gilbert et al., 2006; Holmes & Wolff, 2012; Roberson et al., 2008) and RTs mirrored the pattern of the N2 component, showing a nonlateralized CP effect.

The linguistic nature of categorical perception

The observed main effects of category and interactions of category with visual field in behavior and ERPs suggest that

any linguistic categorization can lead to CP. Semantic content in addition to verbal labels did not enhance CP, replicating a related previous study (Maier et al., 2014). Therefore, the linguistic representations driving CP do not seem to be an amalgam of verbal labels and explicit semantic knowledge associated with a category. Rather, the existence of linguistic categories, no matter what information they are based on, seems crucial. The present results therefore also do not provide further support for the idea that verbal labels take on a special role in CP (Lupyan, 2012; Holmes & Wolff, 2012). Label-advantages might be restricted to situations in which linguistic representations are activated before perception (Boutonnet & Lupyan, 2015; Lupyan, Thompson-Schill, & Swingle, 2010). There is yet a limitation to this conclusion. We excluded participants who made up labels for objects to be learned without names, but participants may still have used key phrases (e.g., “egg breeding device”) to memorize object functions. These could serve as a kind of label—although inconsistent and much less rehearsed than the actual verbal labels. Presently, we can state that well-rehearsed object names are not significantly better at inducing CP than learning which objects fulfill the same function and (potentially) remembering a key phrase describing that function. The learning design presented can be adapted to address follow-up research questions. For instance, do more nameable category labels work better than less nameable ones? Or what effect does categorization based on any arbitrary symbols (e.g., “A” and “B”) have, symbols that are not as unique as object names or semantic information?

Semantic knowledge had an influence on ERPs of its own, namely the N2 (Maier et al., 2014) and the N400 (Abdel Rahman & Sommer, 2008). Therefore, the lack of a direct influence of semantic knowledge on neural and behavioral markers of CP cannot be explained by insufficient learning of the semantic information. Both, categorical and semantic knowledge influenced the N2 component, but these seem to be parallel influences. In contrast to previous findings (Abdel Rahman & Sommer, 2008), in-depth semantic knowledge did not influence the P1 component. Such early perceptual effects of semantic knowledge seem to depend on tasks emphasizing recognition (Abdel Rahman & Sommer, 2008; Lupyan, 2017) and are boosted under perceptually difficult conditions (Abdel Rahman & Sommer, 2008; Maier, Frömer, Rost, Sommer, & Abdel Rahman, submitted). Given that visual search involves discrimination of stimuli, categorical rather than semantic information seems primarily task-relevant.

However, the depth of semantic knowledge may influence the lateralization of CP. In RTs and the N1 component, we observed three-way interactions of visual field, category, and semantic knowledge. In RTs, nested models revealed that semantic knowledge in addition to verbal labels was associated with CP in the LVF. In the N1 component, semantic knowledge seemed to extend the CP effect to the LVF. Future

research should further explore the relationship between the meaningfulness of categories and the lateralization of CP.

The results in the light of the current debate on top-down effects on perception

In their critique of studies reporting top-down effects on perception, Firestone and Scholl (2016) discuss six “pitfalls” that any study reporting a top-down effect should address (which, they write, no study has so far achieved). We fully agree that the question of whether cognition affects perception deserves the highest standard of experimental design strategies. We give a brief summary of how our study design addressed Firestone and Scholl’s points and where we still see limitations.

By ensuring that identical stimuli were tested equally often in all experimental conditions across participants, the balanced learning design addressed two pitfalls. First, it dealt with the caveats of purely confirmatory research strategies (Pitfall 1). Firestone and Scholl (2016) criticized that, besides reporting putative top-down effects where they are expected, studies rarely demonstrate that effects are not observed when their absence is expected. Here, this was implicitly addressed in the learning design. Across participants, each object pair was tested in all experimental conditions. This way, the experiment tested not only the expected presence of a given effect (e.g., between-categories facilitation), but also its opposite (e.g., within-category inhibition) on identical material. Second, with identical stimuli tested in all conditions, the learning design eliminated low-level differences between conditions (Pitfall 4).

Furthermore, we aimed to mitigate the potential influence of task demands and response bias (Pitfall 3). To this end, we asked participants to recall learned category and semantic information only after completion of the visual search task. In the debriefing questionnaire, we also collected participants’ impressions of the experiment, which gave us no reason to believe that the study’s purpose of testing categorical perception was obvious. In addition, a potential high-level response bias would not affect early stimulus-evoked visual ERP components, but later components related or close to the response.

The remaining pitfalls have to do with locating effects in perceptual processing, as opposed to post-perceptual judgment (Pitfall 2), peripheral effects of attention changing the input to perception (Pitfall 5), and “back-end” memory or recognition (Pitfall 6). Here, the main strategy to address these points was the use of ERPs. ERPs effectively differentiated between early perception and higher-level effects such as post-perceptual judgment, potential back-end memory effects or response bias. The onset of CP effects was indeed within early perception (starting in the P1 component; Raftopoulos, 2017). In addition, the experimental design also addressed these three pitfalls. Regarding perception versus judgment (Pitfall 2), Firestone and Scholl (2016) recommended performance-based measures and brief presentation times, both of which were implemented here. With regard to

Pitfall 5, effects should not be attributable to differences between conditions concerning the locations, features or objects participants focus on. As described in the introductory section (“Disentangling perception from other processing stages”), the task design took care to eliminate peripheral, pre-perceptual shifts of attention by avoiding cues and making stimulus displays unpredictable. Concerning memory and recognition (Pitfall 6), Firestone and Scholl pointed out that effects should not be attributable to, for instance, memory load influencing how participants report a stimulus (“back-end” effect), but to how the stimulus is processed perceptually (“front-end”). They recommended directly varying reliance on memory or actively testing irrelevant categories of stimuli. Here, learned categories and semantic knowledge were irrelevant to the visual search task and memory load was the same in all conditions. To summarize, the experimental design and ERPs combined addressed all of the pitfalls discussed by Firestone and Scholl (2016). Still, we see certain limitations to what the results of this experiment can tell us about the nature of top-down effects.

Limitations

Given the learning design, the present results can be interpreted causally—learning new linguistic categories for objects induces differences in early visual processing and object discriminability that are measurable two days later. However, taken alone, the present data are limited in showing the *synchronic* causal influence of language on perception. This would mean that linguistic categories are activated concurrently with perceptual processing and directly modulate ongoing perception during visual search (Lupyan, 2012). Alternatively, the influence of language could happen during learning only: linguistic categorization could enhance changes to visual object representations in long term memory during learning, which would become apparent in visual discrimination two days later (i.e., a *diachronic* effect of language). These mechanisms are not mutually exclusive and may well both apply.

There is converging evidence for synchronicity. First, a linguistic influence during learning alone would not account for the lateralization of CP to the RVF during early visual processing (Maier et al., 2014). Long-term changes to visual object representations should not affect only one half of the visual environment. Rather, the observed RVF lateralization of CP in early visual processing bears similarities with visual processing of linguistic material (Rossion, Joyce, Cottrell, & Tarr, 2003), suggesting an online influence of language on object perception. More converging evidence for synchronicity comes from studies showing that verbal interference affects CP online (Gilbert et al., 2006; Roberson & Davidoff, 2000; Winawer et al., 2007) and that Greek speakers’ increased sensitivity to differences between shades of blue fades away as they live in the United Kingdom and speak English in everyday life (Athanasopoulos, Dering, Wiggert, Kuipers, &

Thierry, (2010). However, it is to date unclear whether verbal interference cancels out CP at the early processing stage investigated here or post-perceptually. Future research should aim to better understand the causal mechanisms at the synchronic level, that is, how exactly linguistic representations shape perception while it happens. This should take the neural dynamics between language areas and visual areas of the brain into account (Tomasello, Garagnani, Wennekers, & Pulvermüller, 2017).

Conclusions

In line with cognitive penetrability of perception, our results suggest that CP can be a genuine top-down effect on visual perception. Using a carefully balanced learning design and ERPs, this study showed that linguistically induced CP involves modulations of neural signatures of early visual processing that cannot be accounted for by pre-perceptual shifts of attention. Furthermore, CP is possible as soon as we acquire linguistic or semantic knowledge that allows forming conceptual stimulus categories. Whether this is also reflected in behavioral measures, such as RTs depends, in our opinion, on task difficulty (Constable & Becker, 2017; Regier & Xu, 2017). In line with a hierarchical predictive processing account of perception, linguistic category information may inform perceptual predictions and directly enhance perception (Clark, 2013; Friston, 2009; Lupyan & Clark, 2015), especially in difficult tasks with high perceptual uncertainty (Regier & Xu, 2017). A synchronic effect of language on perception seems likely given lateralization of early effects to the RVF and converging evidence from verbal interference studies (Gilbert et al., 2006; Roberson & Davidoff, 2000; Winawer et al., 2007). However, the exact mechanisms by which linguistic representations influence perceptual processing online remain to be further described.

Acknowledgements This work was supported by a grant from the German Research Foundation (grant number AB 277- 6) to Rasha Abdel Rahman. Martin Maier was supported by scholarships granted by the State of Berlin and the Berlin School of Mind and Brain. The authors thank Julia Baum and Hannah Klouth for their help with data collection and Guido Kiecker for technical advice and task programming.

Authors' contributions Both authors developed the study design, discussed the results, and wrote the manuscript. M.M. collected and analyzed data.

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