Native language promotes access to visual consciousness

Martin Maier and Rasha Abdel Rahman

Humboldt-Universität zu Berlin

Word count

Abstract: 148

Introduction & Discussion, Notes, Acknowledgments, Appendices: 1993

Number of References: 38

Author note

Martin Maier, Department of Psychology and Berlin School of Mind and Brain, Humboldt-Universität zu Berlin.

Rasha Abdel Rahman, Department of Psychology and Berlin School of Mind and Brain, Humboldt-Universität zu Berlin.

This work was supported by the German Research Foundation (grant number AB 277-6) to Rasha Abdel Rahman. Martin Maier was supported by the State of Berlin with an Elsa Neumann Scholarship and the Berlin School of Mind and Brain.

Correspondence concerning this article should be addressed to Martin Maier, Department of Psychology, Humboldt-Universität zu Berlin, Rudower Chaussee 18, 12489 Berlin, Germany.

Contact: martin.maier@hu-berlin.de, Phone: +49-(0)30-2093-9365

Abstract

Can our native language influence what we consciously perceive? While evidence accumulates that language modulates visual discrimination, little is known about the relation between language structure and consciousness. We employed EEG and the attentional blink paradigm in which targets are often unnoticed. Native Greek speakers (*N*=28), who distinguish categorically between light and dark shades of blue, showed boosted perception for this contrast compared to a verbally unmarked green contrast. Electrophysiological signatures of early visual processing predicted this behavioral advantage. German speakers (*N*=29), placing the "Greek" blues into one category, showed no differences between blue and green targets. The behavioral consequence of categorical perception was replicated with Russian speakers (*N*=46), confirming reproducibility of this novel finding. We conclude that linguistic enhancement of color contrasts provides targets with a head start in accessing visual consciousness. Our native language is thus one of the forces that determine what we consciously perceive.

Keywords: Categorical Perception of Colors, Event-related Potentials, Attentional Blink Effect, Top-down, Linguistic Relativity

Native language promotes access to visual consciousness

The interplay between language and color perception has been one of the most striking examples of linguistic relativity, suggesting that language influences perception (Wolff & Holmes, 2011). For instance, stimuli from different linguistic categories are easier to discriminate than stimuli from the same category (categorical perception, CP; A. L. Gilbert, Regier, Kay, & Ivry, 2006; Goldstone & Hendrickson, 2010; Winawer et al., 2007; but see Brown, Lindsey, & Guckes, 2011). Current theories propose transient categorical warping of perceptual space due to the activation of categories via verbal labels (Lupyan, 2012), tuning perception to features that are relevant for the given category (Cukur, Nishimoto, Huth, & Gallant, 2013; C. D. Gilbert & Li, 2013). Here we investigate whether language affects not only how, but also if we perceive a stimulus in the first place: Can the structure of our native language influence visual consciousness?

Only a fraction of the visual stimuli we are presented with reach conscious perception. Identifying the factors beyond immediate sensory processing that influence what we consciously perceive is essential for a comprehensive understanding of human sensation and perception. Here we employed the attentional blink (AB) paradigm (Raymond, Shapiro, & Arnell, 1992) to demonstrate that linguistic categories, like the color words of our native language, are one such factor. While physically, the wavelengths of light humans perceive as colors form a smooth continuum, different languages categorize colors differently (Regier & Kay, 2009).

We used event-related potentials (ERPs) of the EEG to uncover electrophysiological correlates of CP and relate brain activity to visual consciousness. CP entails modulations of early visual ERP components. Specifically, the P1, reflecting sensory processing in extrastriate visual cortex (Di Russo, Martinez, Sereno, Pitzalis, & Hillyard, 2002), varies as a function of linguistic categories for colors (Forder, He, & Franklin, 2017; Thierry et al.,

2009) and objects (Maier, Glage, Hohlfeld, & Abdel Rahman, 2014). Thierry et al. (2009) measured ERPs in response to standard-deviant stimulus pairs of light and dark green or blue in an oddball paradigm. For Greek speakers, the shades of blue crossed a linguistic boundary whereas they fell into the same category for English speakers. Greek speakers showed distinctive ERP responses to blue deviants in the P1 component and the visual mismatch negativity, peaking around 200 ms, indicating that color categories are reflected in sensory stages of perception and influence brain processes relevant for visual discrimination.

We adapted established color stimuli (Thierry et al., 2009) for an AB paradigm, in which two targets, T1 and T2, are presented within a rapid serial visual presentation stream (RSVP). Detection rates of T2 vary as a function of the lag between T1 and T2 (e.g., 3 vs. 7 pictures), with better performance at long relative to short lags (Martens & Wyble, 2010). Electrophysiological studies showed that the disruption of visual processing occurs relatively late, while early stages up to around 150 ms post-stimulus unfold similarly for detected and missed targets (Sergent, Baillet, & Dehaene, 2005; Vogel, Luck, & Shapiro, 1998). Later stages after 200 ms, associated with attentional selection or visual working memory encoding, are strongly affected. The earliest robust correlate of the “blink” is the N2 component (Sergent et al., 2005) that may reflect competition between T1 and T2 for visual consciousness.

If one’s native language provides different basic-level terms for two colors, linguistic warping should increase the salience of this color contrast. More salient stimuli, in turn, are more prone to enter conscious perception (Chua, 2005; Itti & Koch, 2001; Shapiro, Caldwell, & Sorensen, 1997). Thus, for Greek speakers who apply the categories *ble* and *galazio*, a stimulus containing these shades of blue should have increased salience and get an advantage in the competition for visual consciousness. Based on these assumptions, we aimed to demonstrate a new effect of linguistic categories on perception: that the linguistic color code one has learned influences the chances of seeing or missing a stimulus.

Experiment 1

We tested Greek native speakers, expecting to replicate an AB effect with lower T2 detection rates in the lag 3 compared to the lag 7 condition. If more salient color contrasts help to overcome the AB, hit rates should be highest in a mixed green and blue color condition, containing a stronger chromatic difference. Crucially, Greek speakers should perform better for T2 targets containing blue compared to green contrasts, helped by the linguistic category boundary between *ble* and *galazio*.

In ERPs, we expected the onset of CP—a divergence between blue and green targets—in the P1 component. Both, the mixed and the blue contrast should facilitate attentional selection reflected in the N2 component. Additionally, neural signatures of CP should predict detection behavior. For instance, the early sensory CP signal (P1 component) could increase the chances of blue targets to reach visual consciousness and boost perception.

Method

Participants. Thirty-four healthy participants with normal or corrected-to-normal vision and normal color-vision according to the short version of Ishihara's test for color deficiency (Ishihara, 2014) volunteered for the study. They were native Greek speakers who had been monolingual at least until the age of five. We chose Greek speakers specifically because they make a basic-level distinction between light and dark shades of blue (Athanasopoulos, 2009). This means that the exact meaning of the English word "blue" is not expressible in Greek, and speakers must obligatorily differentiate between light and dark blue (Winawer et al., 2007). English speakers, in comparison, can optionally differentiate between light and dark blue by using non-basic-level terms (e.g. sky blue). Participants provided written informed consent prior to participation. The study was conducted according to the principles expressed in the Declaration of Helsinki and was approved by the local Ethics Committee. Participants received either course credit or monetary compensation of 8 € per hour.

To the extent feasible, we aimed to recruit participants with a short stay in Germany and little German skills, and indicated so on recruitment flyers. However, no participants were excluded based on the time spent in Germany or their proficiency in German. On average, participants had spent two years (*M* = 24.48 months) in Germany (*SD* = 23.85, range 2–110 months). Data from four participants were excluded based on predefined task performance criteria (below 50% T1-performance or above 50% false alarms in target-absent trials in the lag 3 condition). Data from another two participants were excluded based on their individual color naming (sorting light and dark blue into the same category). We chose (conservatively) not to exclude participants sorting the green stimuli into different categories even though this may dilute the CP effect. The final sample consisted of 28 participants (15 female), aged *M* = 28.00 years (*SD* = 4.44) and right handed.

Planning of the sample size was based on a behavioral pilot study with eight participants in which bottom-up contrast was manipulated in gray scale stimuli. The pilot study yielded a *b* coefficient of 0.20 for the effect of contrast on hit rates. Assuming a considerably smaller coefficient of 0.15 for a top-down color contrast, we ran a simulation using the SIMR package in R (Green & MacLeod, 2016) to estimate the expected power to secure the fixed effect of *color contrast* given different sample sizes. With 500 randomizations, the simulation showed that a sample size of 25 would be needed to achieve

82% (CI[1] [78.5, 85.5]) power. For good EEG data quality, we aimed for a higher sample size of about 30 participants.

Procedure. All participants filled in a questionnaire about their language experience and proficiency (LEAP-Q; Marian, Blumenfeld, & Kaushanskaya, 2007) before the experiment. Participants received the consent form and all written instructions before and during the AB task in Greek. During EEG preparation, interaction with the participants in German or English was kept at a minimum and participants read a book or browsed the Internet in Greek. For the AB task, participants were seated in a dark, shielded and sound attenuated test cabin. After the task, all participants remained seated and freely named the four colors involved in the experiment. Next, to confirm language-typical color categorization, they were shown two slides with 15 blue and then 15 green stimuli, including the stimuli used in the task, and asked to assign them to categories.

In the AB task, two targets, T1 and T2, were to be detected in a RSVP stream of distractors (see Figure 1). Each participant performed 528 trials. In each trial, following a 450 ms fixation cross, 13 shapes were presented for 41 ms each with blank screens of 53 ms in between. Participants looked for the occurrence of a semi-circle (T1) and a triangle (T2). T1 always occurred, whereas T2 was absent in 18.2% of the trials. T2-absent trials served to estimate the false alarm rate of each participant and to subtract EEG-activity unrelated to the processing of T2 for plotting purposes. The position of T2 was either seven (lag 7) or three pictures after T1 (lag 3). After each RSVP stream, participants were asked to successively report the direction of the semi-circle and—if present—the direction of the triangle, and to rate the subjective visibility of the triangle on a 4-point scale (“nothing”, “slight impression”, “strong impression”, “complete”).

[1] CI = 95% confidence interval

All trial types (lags 3 or 7, T2 present or absent, different color conditions) were presented in randomized order. Lag 3 trials were more frequent than lag 7 trials (86.4% vs. 13.6% of T2 present trials) because this is where a strong AB effect was expected. Lag 3 trials were thus more informative about electrophysiological processing associated with access to visual consciousness. In order to keep the experiment duration as short as possible, we therefore decided to increase the relative frequency of lag 3 trials.

Materials. Stimuli were presented on a calibrated 19-inch LCD monitor with a 75-Hz refresh rate and a resolution of 1280 × 1024 pixels, positioned at a distance of 70 cm to the participants' eyes. The monitor was switched on at least one hour before experiment start to ensure correct color presentation. Distractors and targets were geometric shapes on a colored background circle subtending 2.9° visual angle (see Figure 1). T1-stimuli were gray semi-circles, with the round side pointing either up or down. T2-stimuli were colored triangles, pointing either to the left or to the right. Distractor shapes were gray polygons other than semi-circles or triangles (13 different shapes).

The crucial color contrast manipulation was implemented in the contrast between the triangle's color and the background circle's color (Figure 1c): light blue vs. dark blue (in the following referred to as: blue contrast), light green vs. dark green (green contrast), and light/dark blue vs. light/dark green (mixed contrast). The green contrast was measured to be equally salient as the blue contrast (Thierry et al., 2009). The mixed contrast served as a manipulation check: in addition to crossing a category boundary, it contained a stronger bottom-up chromatic difference than the two other contrasts. This allowed us to simultaneously assess the effects of top-down (linguistic) and bottom-up color contrast.

We reproduced the Munsell-colors used in the studies by Athanasopoulos (Athanasopoulos, 2009) and Thierry et al. (Thierry et al., 2009), measured with a ColorCAL MKII Colorimeter (Cambridge Research Systems). These were (CIE 1931 chromaticity coordinates x, y, and luminance Y are given in parentheses): dark blue 5PB/value 4 (x=.234, y=.230, Y=10.8), light blue 5PB/value 7 (x=.259, y=.264, Y=41.7), dark green 5G/value 4 (x=.259, y=.397, Y=10.6), and light green 5G/value 7 (x=.279, y=.377, Y=41.5) with constant Munsell chroma 6 (saturation). The distractor shapes were rendered in gray tones fitted in luminance to the light and dark colors: dark gray (x=.312, y=0.321, Y=10.7) and light gray (x=.312, y=0.321, Y=41.7). The monitor background was middle gray (x=.312, y=0.321, Y=36.5).

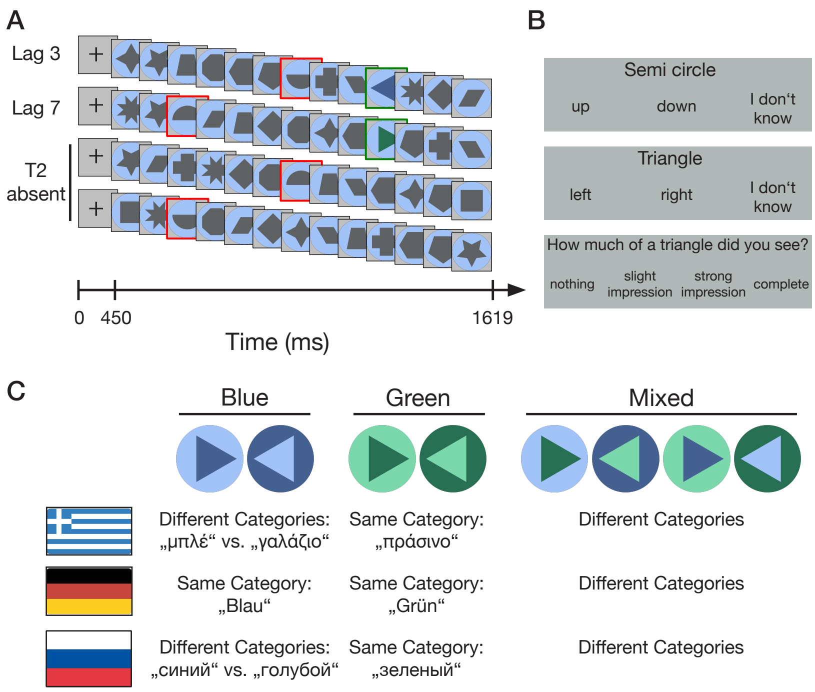

Figure 1. Illustration of the AB task. (A) RSVP trial sequence. Participants attended to semi-circles (T1) and triangles (T2). In all T2 present trials, T2 occurred at Position 10 in the RSVP stream (highlighted in green for illustration). The positions of T1 in lag 3 and lag 7 trials are highlighted in red. The lags between T1 and T2 corresponded to 282 ms in lag 3 and 658 ms in lag 7. In T2-absent trials, only T1 occurred. (B) Response displays. After each RSVP, participants answered a sequence of three forced-choice questions from which we derived whether a trial was a hit or a miss. (C) T2 stimuli. Each of the color contrasts blue,

green and mixed occurred equiprobably and with triangles pointing in both directions. Crucially, for Greek and Russian speakers (Experiments 1 and 3), the blue stimuli fall into different basic-level categories. For German speakers (Experiment 2) there is no basic-level linguistic contrast.

Analysis of behavioral data. Behavioral data were analyzed with binomial generalized linear mixed models (GLMMs), given that hit rates in the AB task followed a binomial distribution. Analyses were done in R (R Core Team, 2014) using the lme4 package (Bates, Mächler, Bolker, & Walker, 2014) and the lmerTest package (Kuznetsova, Brockhoff, & Christensen, 2016) to calculate *p*-values. GLMMs comprised the fixed factors lag, and color contrast, modeled as sliding difference contrasts. Sliding difference contrasts compare the means of adjacent levels of a fixed factor (e.g., lag 3 vs. lag 7). In order to test all three levels of the factor color contrast against each other, models were run with two different factor level orders, i.e. green-blue-mixed and blue-green-mixed. Models corrected for by-participant random intercepts and, where applicable, random slopes for the within-subjects factors lag and color contrast. Random effects structures were determined using singular value decomposition, removing random slopes that prevented model convergence or explained zero variance, in order to avoid overparameterization. Fixed effects structures were optimized using the anova function of the stats package in R and based on the Akaike information criterion (AIC) and the Bayesian information criterion (BIC), which decrease with increasing model fit. We used the keepef function from the remef package (Hohenstein & Kliegl, 2015) to compute predicted partial effects for illustration.

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-cut-off filters (0.032 Hz and 1000 Hz) were applied and all electrodes were referenced to the left mastoid. Electrode impedance was kept below 5 kΩ. Electrooculograms were recorded from electrodes next to both eyes and from above and below the left eye. After the main experiment, participants made prototypical eye movements in a calibration procedure for later artifact correction. Offline preprocessing steps were made in MATLAB 2014a using the EEGLAB toolbox (Delorme & Makeig, 2004). 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 µV or changing by more than 50 µV between two successive samples or by 200 µV within intervals of 200 ms). Artifact-free data were segmented into epochs of 1 s, time-locked to the onset of T2, 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 T2 onset. Single-trial ERPs were time-locked to the onset of T2, averaged across time windows of interest and, after confirming normal distribution, subjected to LMMs (Frömer, Maier & Abdel Rahman, 2018). We tested for associations between the fixed factor color contrast (modeled as sliding difference contrast) and mean ERP amplitudes in a predefined posterior region of interest (ROI; see Results section). We chose LMMs mainly because participants differed in the strength of the behavioral AB effect, which led to unequal numbers of hit trials across participants entering the ERP-analysis. LMMs are robust against differences in trial numbers across participants because they allow correcting for by-participant random intercepts as well as random slopes regarding the influence of the fixed effects (Baayen, Davidson, & Bates, 2008). Models corrected for by-participant random intercepts and, where applicable, random slopes for the within-subjects factor color contrast. Random effects structures were determined using singular value decomposition, removing random slopes that prevented model convergence or explained zero variance. Model selection was based on likelihood ratio tests, as well as AIC and BIC. Data and code used for all analyses can be accessed at osf.io/sqp6z.

Results

Color naming. All participants in the final sample sorted light and dark blue stimuli into different basic color categories (Figure 2). Most participants (75.0%) placed light and dark green stimuli into the same category.

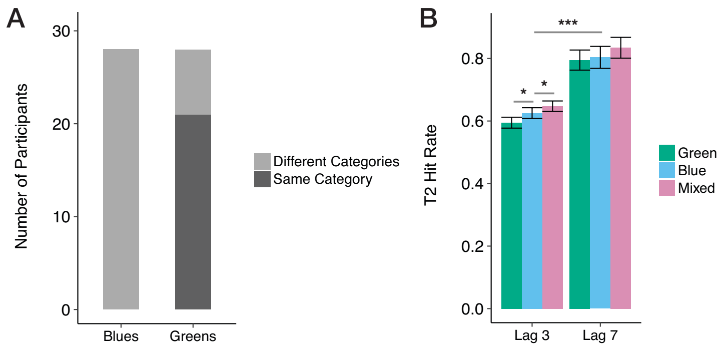

*Figure 2***.** Experiment 1: behavioral results. (A) Color naming pattern, showing how many participants sorted shades of blue and the shades of green into the same category vs. different categories. (B) AB task performance in Greek speakers: Hit rates per lag and color contrast. Difference between lags 3 and 7: AB effect. Overall and within lag 3, performance was best for the mixed contrast and, crucially, better for the blue compared to the green contrast. Error bars represent 95% CI. Statistical significance codes: *** p<.001, * p<.05.

Behavioral Results. Mean T1 accuracy was $M = 85.8\%$ (CI [85.2, 86.4]). In T2 absent trials, the mean correct rejection rate was $M = 89.0\%$ (CI [87.7, 90.3]). Only T2 present trials in which T1 was correctly identified were selected for further analysis. A trial was considered a hit if both, T1 and T2 were seen and correctly identified (correct report of T1 and at least a "slight impression" and correct direction of T2 reported). We tested for the presence of an AB effect and effects of color contrast on hit rates. Table 1 displays the estimated effect sizes (regression coefficients *b*) of the fixed effects, standard errors, and *z*-values, as well as estimates of the square root of the variance components (*SD*) for this analysis. As shown in Figure 2, mean hit rates differed between lags 3 and 7 (81.1% lag 7 hits, CI [78.6, 83.6] vs. 62.2% lag 3 hits, CI [60.9, 63.5]). Binomial GLMM analysis revealed a main effect of the factor *lag*, i.e. an AB effect. Further, hit rates in the mixed condition were higher than in both the green and the blue contrast conditions across both lags, yielding significant main effects of color contrast (mixed-blue), and color contrast (mixed-green). Crucially, participants accomplished more hits in the blue condition than in the green condition, as confirmed by a main effect of color contrast (blue-green). These results suggest that linguistic categorization benefited T2 detection and classification. There was no interaction of the factors lag and color contrast and removing this interaction did not decrease, but slightly increased model fit (Δ_{AIC} = -3, Δ_{BIC} = -18). Taken together, these results confirm the predicted hit rate pattern depending on color contrast, i.e. mixed > blue > green.

Table 1

Experiment 1: GLMM statistics for mean hit rates

Variable	*b*	*SE*	*z*	*p*
Logit mean hit rate (intercept)	1.128	0.194	5.820	<.001***
Lag(7-3)	1.161	0.139	8.351	<.001***
Color contrast (B-G)	0.122	0.057	2.157	.031*
Color contrast (M-B)	0.166	0.058	2.874	.004**
Color contrast (M-G)	0.289	0.057	5.045	<.001***

Note. B = blue contrast, G = green contrast, M = mixed contrast. Variance components were estimated for Participants (random intercept; *SD* = 1.002) and Lag (random slope; *SD* = 0.594). Goodness of fit measures: Log likelihood = -5557.7, REML deviance = 11115.5. *** $p < .001$, ** $p < .01$, * $p < .05$.

To test the presence of the CP effect also specifically for lag 3, in which the AB effect was observed and to which ERP analyses were restricted (cf. Procedure subsection under Method), we recomputed the same GLMM, but with color contrast nested within lag. As shown in Figure 2, the hit rate in the mixed condition (64.7%) was higher than in the blue (62.5%, b =0.15, z = 2.50, p = .013) and the green condition (59.4%, b = 0.29, z = 4.69, p < .001). Importantly, the statistical difference between the blue and green condition was also observed within lag 3 (b =0.13, z = 2.18, p = .030).

EEG Results. We analyzed effects of the factors color contrast in lag 3 hit trials, focusing on components associated with early visual processing (P1) and encoding of targets into visual working memory (N2). For both components, we selected a posterior ROI consisting of electrodes Oz, O1, O2, POz, PO3, PO4, PO7, and PO8. On average, the P1 peaked between 100 and 140 ms and the N2 peaked between 220 and 300 ms.

In the P1, mean amplitude was larger in the blue compared to the green and the mixed condition (Figure 3). Table 2 displays the regression coefficients *b* of the fixed effects, standard errors, and *t*-values, as well as estimates of the square root of the variance components (*SD*) and goodness-of-fit parameters of the LMM analysis. The LMM revealed a significant effect of color contrast (blue-green). There was no significant effect of color contrast (mixed-green) and a statistical trend for the effect of color contrast (mixed-blue).

In the N2, mean amplitudes in both the mixed and the blue condition were reduced compared to the green condition (see Figure 4). The LMM analysis revealed effects of color contrast (mixed-green), and color contrast (blue-green), and no effect of color contrast (mixed-blue) (see Table 2).

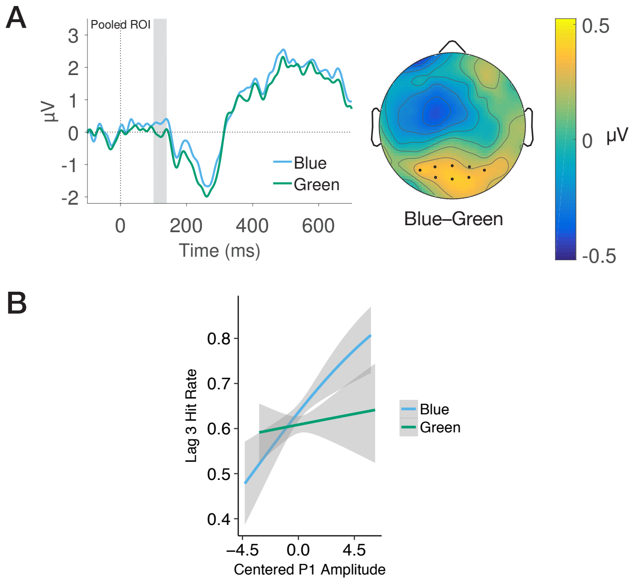

Figure 3. Experiment 1: ERP results in the P1 component. (A) ERP curves for hits in the blue and green color contrast conditions with topographical difference map (blue–green). P1 was larger for the blue compared to the green contrast. For better recognizability of ERP components, ERP curves are plotted with the T2 absent condition subtracted from each curve, removing most of the activity related to T1 processing and noise resulting from the RSVP. ROI-electrodes are marked as dots. (B) Predicted partial effect illustrating the association between P1 and task performance (interaction of P1 amplitude × color contrast). The larger P1 for blue compared to green targets was significantly associated with lag 3 hit rates. Note that regression lines are not necessarily straight because logit-transformed hit rates were back transformed for plotting. Gray shading indicates 95 % CI.

To specifically test the association between the effects of color contrast in ERPs and detection behavior, we entered P1 amplitude and N2 amplitude as covariables in a binomial GLMM to predict hit rates. There were main effects of both, P1 amplitude (b = 0.09, z = 2.93, p = .003) and N2 amplitude (b= -0.28, z = -8.79, p < .001). Further, there was an interaction of color contrast (blue-green) × P1 amplitude (b = 0.14, z = 2.19, p = .029). This means that the larger P1 in processing blue compared to green targets was associated with facilitated conscious perception of T2. Figure 3b illustrates the predicted partial effect of this interaction. There were no interactions between color contrast and N2 amplitude and removing them improved model fit (Δ_{AIC} = -7.3, Δ_{BIC} = -36.2).

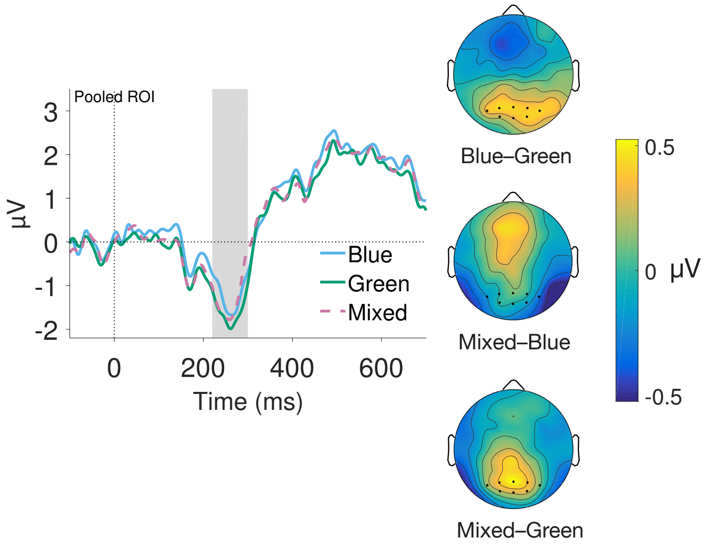

Figure 4. Experiment 1: ERP results in the N2 time window. ERP curves for hits in the blue, green, and mixed color contrasts with topographical difference maps. Significant differences were observed between the blue and the green condition, as well as the mixed and the green condition. As in Figure 3, the ERP of the T2 absent condition was subtracted from each curve for better recognizability of ERP components.

Table 2

Experiment 1: LMM statistics for mean ERP-amplitudes in the P1 and N2 time windows

	P1				N2			
Variable	*b*	*SE*	*t*	*p*	*b*	*SE*	*t*	*p*
Mean amplitude (intercept)	1.086	0.276	3.935	<.001***	-0.393	0.216	-1.817	.080
Color contrast (B-G)	0.318	0.154	2.069	.039*	0.369	0.146	2.529	.012*
Color contrast (M-B)	-0.273	0.151	-1.805	.071	-0.084	0.143	-0.589	.556
Color contrast (M-G)	-0.045	0.152	0.297	.766	0.284	0.144	1.972	.049*

Note. B = blue contrast, G = green contrast, M = mixed contrast. Variance components in the model for P1 amplitudes were estimated for Participants (random intercept; *SD* = 1.409) and Residuals (*SD* = 4.333). Variance components in the model for N2 amplitudes were estimated for Participants (random intercept; *SD* = 1.087) and Residuals (*SD* = 4.115). Goodness of fit measures (P1): Log likelihood = -14163.4, REML deviance = 28326.9. Goodness of fit measures (N2): Log likelihood = -13905.1, REML deviance = 27810.2. *** $p < .001$, * $p < .05$.

Discussion

Results showed a classical AB effect. As predicted, the increased chromatic stimulus contrast in the mixed condition benefited T2 detection. Crucially, the linguistic distinction of light and dark shades of blue enhanced detection rates compared to the matched green contrast.

ERPs revealed further evidence for CP effects on visual consciousness. The blue and green contrast conditions diverged in the P1 and N2 components. Additionally, we observed an effect of the mixed compared to the green contrast in the N2. The P1 effect is in line with previous studies (Forder at al., 2017; Maier et al., 2014; Thierry et al., 2009), extending evidence on CP in early visual processing to the AB paradigm. The early onset in the P1 suggests that CP can indeed be a genuine perceptual effect.

The N2 showed relative amplitude reductions in color contrasts associated with higher T2 hit rates, i.e. mixed and blue compared to green. This time window being crucial for visual consciousness, this suggests a link between detection behavior and electrophysiological differences in the processing of T2s with different color contrasts.

We specified the relation between electrophysiological signatures and behavior by testing the predictive value of the ERP effects for T2 detection. P1 and N2 amplitudes predicted conscious perception of T2. Whereas the association of the N2 and the AB effect is well established, the P1 has not been seen as a primary correlate of conscious perception in the AB (Sergent et al., 2005). This might be different here because of the color contrast manipulation. Indeed, as a core finding, the larger P1-amplitude for T2s in the blue compared to the green condition predicted T2 detection. To our knowledge, this establishes the first direct link between early neural signatures of CP and a perceptual benefit. Linguistic modulations of early visual processing thus have the potential to induce behavioral changes. We argue that color terminology increased the salience of the blue contrast in native Greek speakers due to linguistic warping of perceptual space, facilitating recognition of visual features (e.g., of a triangle). This should provide blue T2s with a head start in the competition for visual consciousness.

Experiment 2

In Experiment 1, the green contrast was used as a control condition for the blue contrast, measured to be equally salient according to the Munsell color system as in previous studies (e.g., Thierry et al., 2009). Thus, with the green contrast as a control, Experiment 1 is a valid test of CP. However, inaccuracy of measuring or the Munsell color system itself could still induce differences in bottom-up salience, independent of linguistic categories. To rule out this alternative, we replicated the experiment with native German speakers who make no basic-level distinction between the two shades of blue. They should show an equal AB effect for blue and green stimuli in behavior and electrophysiological correlates. Reduced AB effects in the chromatically more salient mixed condition observed in Experiment 1 should be replicated.

Method

All materials, EEG recording and data analysis were as in Experiment 1.

Participants. Thirty-eight healthy participants with normal or corrected-to-normal vision and normal color-vision volunteered for the study. Participants were native German speakers who had been monolingual at least until the age of five. They provided written informed consent prior to participation. The study was conducted according to the principles expressed in the Declaration of Helsinki and was approved by the local Ethics Committee. Participants received either course credit or monetary compensation of 8 € per hour. Data from five participants were excluded based on predefined task performance criteria (below

50% T1-performance or above 50% false alarms in target-absent trials in the lag 3 condition). Data from another four participants were excluded based on their individual color naming (sorting light and dark blue into different categories). Importantly, while German native speakers can of course distinguish verbally between shades of blue (e.g., sky blue, ultramarine blue, etc.), unlike in Greek or Russian, there is only one basic-level category. Greek and Russian speakers *have to* verbally distinguish light and dark blue (Winawer et al., 2007). The final sample consisted of 29 participants (15 female), aged $M = 27.03$ years ($SD = 4.76$) and right handed.

Procedure. Experiment 2 followed the same procedure as Experiment 1, except that all written forms and instructions were given in German.

Results

Color naming. All participants in the final sample placed light and dark blue stimuli into the same category (Figure 5). Similar to the Greek speakers of Experiment 1, most of the participants (79.3%) placed the green stimuli into the same category.

Behavioral results. Mean T1 accuracy was $M = 83.1\%$ (CI [82.5, 83.7]). In T2 absent trials, the mean correct rejection rate was $M = 92.0\%$ (CI [90.9, 93.1]). General task performance was thus comparable to Experiment 1. Only T2 present trials in which T1 was correctly identified were selected for further analysis. We first tested for the presence of an AB effect and effects of color contrast on hit rates. Table 3 displays the model estimates for this binomial GLMM analysis. In line with an AB effect, mean hit rates differed between lags 3 and 7 (80.9% lag 7 hits, CI [78.3, 83.5] vs. 58.8% lag 3 hits, CI [57.5, 60.1]; Figure 5). Hit rates in the mixed contrast condition were higher than in both the green and the blue contrast conditions, yielding significant main effects of color contrast (mixed-blue) and color contrast (mixed-green). Crucially, there was no effect of color contrast (blue-green). This pattern was confirmed within lag 3, with a higher hit rate in the mixed condition (60.3%) compared to the blue condition (58.0%, b = 0.14, z = 2.18, p = .030) as well as the green condition (58.2%, b = 0.12, z = 1.97, p = .049). As predicted, there was no difference between the blue and the green condition (b = -0.01, z = -0.21, p = .832).

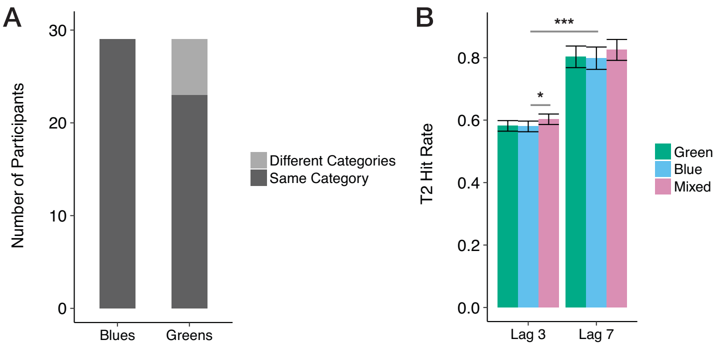

*Figure 5***.** Experiment 2: behavioral results. (A) Color naming pattern, showing how many participants sorted shades of blue and the shades of green into the same category vs. different categories. (B) AB task performance in German speakers: Hit rates per lag and color contrast. Difference between lags 3 and 7: AB effect. Overall and within lag 3, performance was best for the mixed contrast and, crucially, there was no difference between the blue and the green contrast. Error bars represent 95% CI. Statistical significance codes: *** p<.001, * p<.05.

Table 3

Experiment 2: GLMM statistics for mean hit rates

Variable	*b*	*SE*	*z*	*p*
Logit mean hit rate (intercept)	1.001	0.206	4.853	<.001***
Lag(7-3)	1.271	0.164	7.740	<.001***
Color contrast (B-G)	-0.019	0.058	-0.321	.748
Color contrast (M-B)	0.149	0.058	2.559	.011*
Color contrast (M-G)	0.130	0.058	2.242	.025*

Note. B = blue contrast, G = green contrast, M = mixed contrast. Variance components were estimated for Participants (random intercept; $SD = 1.089$) and Lag (random slope; $SD = 0.775$). Goodness of fit measures: Log likelihood = -5449.6, REML deviance = 10899.2. *** $p < .001$, * $p < .05$.

EEG results. On average, the P1 peaked slightly later in Experiment 2 compared to Experiment 1 (120-170 ms vs. 100-140 ms). Entering the same time window as in Experiment 1 (100-140 ms) did not change the pattern of results. As shown in Figure 6 and Table 4, P1 amplitudes did not differ as a function of color contrast.

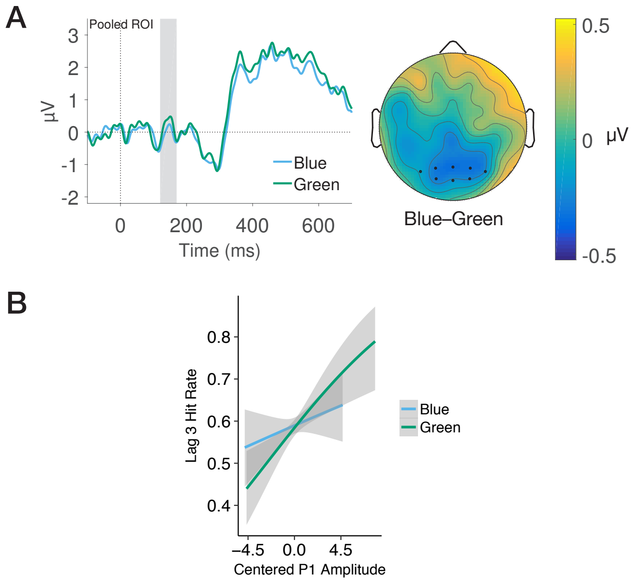

Figure 6. Experiment 2: ERP results in the P1 component. (A) ERP curves for hits in the blue and green color contrast conditions with topographical difference map (blue–green), showing no significant difference. As before, the ERP of the T2 absent condition was subtracted from each curve for better recognizability of ERP components. ROI-electrodes are marked as dots. (B) Predicted partial effect illustrating the association between P1 and task performance, which was not modulated by color contrast (blue-green). Note that regression lines are not necessarily straight because logit-transformed hit rates were back transformed for plotting. Gray shading indicates 95 % CI.

Table 4

Experiment 2: LMM statistics for mean ERP-amplitudes in the P1 and N2 time windows

	P1				N2			
Variable	*b*	*SE*	*t*	*p*	*b*	*SE*	*t*	*p*
Mean amplitude (intercept)	0.374	0.210	1.785	.085	-0.448	0.238	-1.884	.069
Color contrast (B-G)	-0.223	0.160	-1.392	.164	-0.105	0.160	-0.657	.511
Color contrast (M-B)	0.200	0.159	1.258	.208	0.314	0.159	1.976	.048*
Color contrast (M-G)	-0.023	0.159	-0.145	.885	0.209	0.159	1.312	.190

Note. B = blue contrast, G = green contrast, M = mixed contrast. Variance components in the model for P1 amplitudes were estimated for Participants (random intercept; *SD* = 1.048) and Residuals (SD = 4.381). Variance components in the model for N2 amplitudes were estimated for Participants (random intercept; SD = 1.207) and Residuals (SD = 4.338). Goodness of fit measures (P1): Log likelihood = -13232.1, REML deviance = 26464.2. Goodness of fit measures (N2): Log likelihood = -13243.4, REML deviance = 26486.8. * p <.05.

Next, we tested for effects of color contrast on the amplitude of the N2 in the time window between 220 and 300 ms (see Table 4 for detailed results of the LMM analysis). As depicted in Figure 7, N2-amplitude was lowest in the mixed condition. LMM analysis revealed an effect of color contrast (mixed-blue) and no effects of color contrast (mixed-green) and color contrast (blue-green).

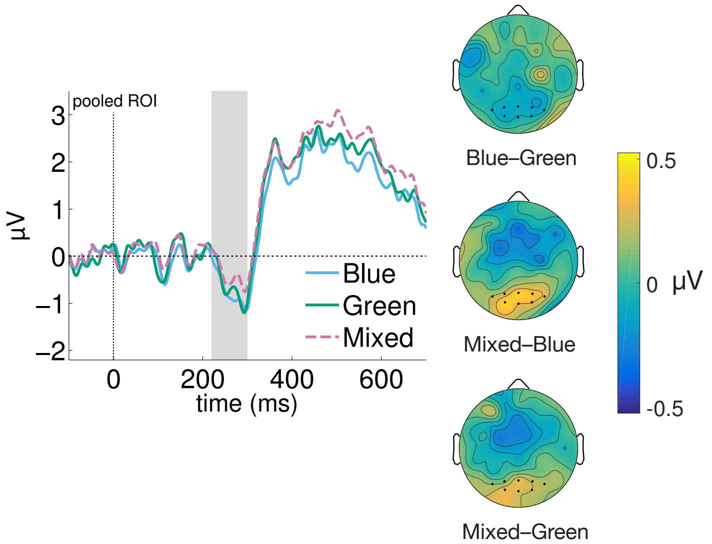

Figure 7. Experiment 2: ERP results in the N2 time window. ERP curves for hits in the blue, green, and mixed color contrasts with topographical difference maps. A significant difference was observed between the mixed and the blue condition. As before, the ERP of the T2 absent condition was subtracted from each curve for better recognizability of ERP components.

Testing for associations between ERP components and behavior revealed main effects of P1 amplitude (b = 0.13, z = 3.93, p < .001) as well as N2 amplitude (b = -0.25, z = -7.82, p < .001), replicating the results of Experiment 1. There were, however, no interactions between color contrast and P1 amplitude or N2 amplitude. Removing the interactions from the formula did not decrease, but increased model fit (Δ_{AIC} = -4.5, Δ_{BIC} = -53.3).

Tables S1 and S2 in the Supplemental Material summarize additional analyses of the ERP data and ERP-behavior associations containing the factor experiment, yielding significant by-experiment interactions for all CP-effects.

Discussion

Experiment 2 revealed no differences between the blue and the green condition in behavior, the P1 component, the N2 component, or the association between P1 and behavior—all of which had been observed in Experiment 1. German speakers did show the expected behavioral advantage in the mixed condition that served as a manipulation check, suggesting that language-independent salience of color contrast had a similar effect in all participants. As in Experiment 1, P1 and N2 were associated with conscious perception of T2, but not differentially for the different color contrasts. Given these results, the CP effects in Experiment 1 cannot be attributed to stimulus confounds.

Experiment 3

To probe the robustness of the novel finding that native language promotes the access to visual consciousness, we ran a preregistered behavioral replication study (osf.io/ke82p). We invited native Russian speakers who also make a basic-level linguistic distinction between light and dark shades of blue (*goluboy* vs. *siniy*; Winawer et al., 2007). We expected to replicate the pattern of hit rates observed in Greek speakers.

Method

Participants. A priori power analysis based on the CP effect size observed in Greek speakers (b = 0.12) yielded an optimal sample size of 45 participants. In order to acquire 45 valid datasets according to the preregistered inclusion criteria, we tested 58 healthy participants with normal or corrected-to-normal vision and normal color-vision. Participants were native Russian speakers who had been monolingual at least until the age of five. They provided written informed consent prior to participation. The study was conducted according to the principles expressed in the Declaration of Helsinki and was approved by the local Ethics Committee. Participants received either course credit or monetary compensation of 8 € per hour. Data from nine participants were excluded based on predefined task performance criteria (below 50% T1-performance or above 50% false alarms in target-absent trials in the lag 3 condition). One participant was excluded due to insufficient T2-performance, detecting only one T2 overall. Data from another two participants were excluded based on their individual color naming (sorting light and dark blue into the same category). The final sample consisted of 46 participants (38 female), aged M = 24.59 years (SD = 5.67) and right handed.

Procedure. Experiment 3 followed the same procedure as Experiments 1 and 2, except that all written forms and instructions were given in Russian and no EEG data were collected.

Results

Color naming. All participants in the final sample placed light and dark blue stimuli into different categories. Naming of green colors was somewhat more varied than in Greek and German speakers in Experiments 1 and 2 (same category for light and dark green in 63.0% of participants, compared to 75.0% and 79.3 %).

Behavioral results. General task performance was comparable to Experiments 1 and 2, with mean T1 accuracy of M = 86.0 (CI [85.5, 86.5]) and mean correct rejection rate of M = 89.8% (CI [88.8, 90.8]). Only T2 present trials in which T1 was correctly identified were selected for further analysis. We tested for effects of lag and color contrast on hit rates. GLMM model estimates are summarized in Table 5. In line with the AB effect, hit rates were lower in the lag 3 condition (63.3%, CI [62.3, 64.3]) than in the lag 7 condition (80.2 %, CI [78.2, 82.2]0). Replicating the results from Experiments 1 and 2, hit rate was highest in the mixed contrast. Crucially, confirming the predicted CP effect, Russian speakers performed better in the blue compared to the green contrast (Table 4). Hit rates per lag and color contrast are illustrated in Figure 8. There was no interaction of lag and color contrast, and excluding the interaction term did not decrease, but increased model fit (Δ_{AIC} = -3, Δ_{BIC} = -19). As in Experiment 1, to confirm the presence of the CP effect specifically for lag 3, we computed the binomial GLMM again with color contrast nested within lag. Confirming the predicted pattern, hit rates were higher in the blue contrast (62.5%) compared to the green contrast (59.6%, b = 0.138, z = 2.958, p = .003), and higher in the mixed compared to the blue contrast (67.8%, b = 0.284, z = 5.951, p < .001). Thus, all predictions were confirmed.

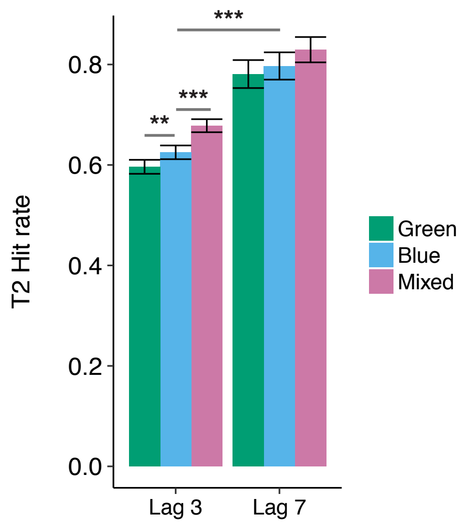

*Figure 8***.** Experiment 3: AB task performance of Russian native speakers. Hit rates per lag and color contrast. Error bars represent 95% CI. Statistical significance codes: *** p<.001, ** p<.01.

Table 5

Experiment 3: GLMM statistics for mean hit rates

Variable	*b*	*SE*	*z*	*p*
Logit mean hit rate (intercept)	1.156	0.147	7.875	<.001***
Lag(7-3)	0.970	0.103	9.417	<.001***
Color contrast (B-G)	0.131	0.044	3.018	0.003**
Color contrast (M-B)	0.279	0.045	6.248	<.001***

Note. B = blue contrast, G = green contrast, M = mixed contrast. Variance components were estimated for Participants (random intercept; $SD = 0.973$) and Lag (random slope; $SD = 0.560$). Goodness of fit measures: Log likelihood = -9288.4, REML deviance = 18576.9. *** $p < .001$, ** $p < .01$.

To test cross-linguistic differences in the influence of color contrast on the AB effect, we analyzed hit rates across Experiments 1 to 3 with the factor language. To this end, Greek and Russian speakers, who distinguish categorically between shades of blue, were grouped together and tested against German speakers. The final GLMM included the factor lag only as a main effect because the model including the interaction term failed to converge. The mixed contrast benefited performance in both language groups, as confirmed by a main effect of color contrast (mixed-blue). Completing the picture of the behavioral results, an interaction of language × color contrast (blue-green) showed that the blue contrast benefited performance in the group of Greek and Russian speakers, but not German speakers. The GLMM estimates are summarized in Table 6.

Table S3 in the Supplemental Material summarizes the results of an additional GLMM analysis of hit rates across Experiments 1 to 3, confirming that the size of the overall AB effect was comparable in all experiments.

Table 6

GLMM statistics for Hit rates with the factor language

Variable	*b*	*SE*	*z*	*p*
Logit mean hit rate (intercept)	1.080	0.113	9.548	<.001***
Language (GrRu-De)	0.116	0.227	0.512	0.609
Color contrast (B-G)	0.055	0.034	1.632	0.103
Color contrast (M-B)	0.193	0.034	5.672	<.001***
Lag (7-3)	1.106	0.077	14.455	<.001***
Language:Color contrast (B-G)	0.147	0.067	2.182	0.029*
Language:Color contrast (M-B)	0.089	0.068	1.308	0.191

Note. GrRu = grouped Greek and Russian speakers, De = German speakers, B = blue contrast, G = green contrast, M = mixed contrast, ":" indicates interactions between factors or covariables. Variance components were estimated for Participants (random intercept; *SD* = 1.014) and Lag (random slope; *SD* = 0.651). Goodness of fit measures: Log likelihood = -20300.6, REML deviance = 40601.1. * $p < .05$, *** $p < .001$.

Discussion

Experiment 3 replicated the findings of Experiment 1 with a different participant group, Russian native speakers. This speaks to the robustness of the behavioral consequence of CP for visual consciousness. Having two different basic-level terms for shades of blue increases the chances of perceiving targets containing this contrast in the AB paradigm.

General Discussion

The present results show for the first time that color CP can facilitate the access of a stimulus to conscious perception. This significantly extends previous reports that verbal cues (e.g., "pumpkin") help bring initially suppressed visual stimuli (e.g., a pumpkin) into consciousness during continuous flash suppression (Lupyan & Ward, 2013). Here, no verbal cues were presented, demonstrating effects of implicitly co-activated linguistic categories.

This rules out explicit verbal priming and, because color contrasts were task-irrelevant, post-perceptual decision-biases.

With a reduction of the AB effect of about 3 % the behavioral CP effect was small but statistically robust and reproducible. Still, the advantage of the mixed over the green condition (containing increased bottom-up and top-down linguistic contrasts) was only around 5 to 8%, setting an upper limit for the purely linguistically induced effects. Furthermore, Greek and Russian speakers lived in Germany at the time of the experiment and 25% of Greek and 37% of Russian speakers sorted the green stimuli into different categories, which may have weakened CP (Athanasopoulos et al., 2010).

The idea that cognitive influences concern perception proper is controversial (Firestone & Scholl, 2015), which is why we measured neural signatures of perceptual processing. EEG and the well-described functional significance of visual ERP components like the P1 provide tools for fine-grained temporal descriptions of different aspects of perception. Here, the effect in the P1 component clearly associates CP with early stages of visual perception (Forder et al., 2017; Maier et al., 2014; Thierry et al. 2009). Our results therefore provide evidence that perception is penetrable to cognitive factors such as categorization based on the language one speaks.

Generalizability

The target population consisted of speakers that were monolingual at least until the age of five. Effects might differ for early bilinguals. Our findings should be generalizable to other color contrasts and languages exhibiting differences in basic-level color terms (e.g. shades of green in Korean; Roberson, Pak & Hanley, 2008). A direct replication should take time spent in the second language environment and second language proficiency into account during recruitment, include only participants actually making the color distinction of interest and “activate” participants’ native language before the main task (cf. Procedure sections). We have no reason to believe that the results depend on other characteristics of the participants, materials, or context.

Conclusions

We extend the literature on the relation between language and perception by describing a new phenomenon: our native language—and the color categories we apply within it—can influence whether we consciously perceive a stimulus or not. A possible mechanism behind this effect is linguistic warping of perceptual space, which enables top-down modulations of the brain processes that lead up to conscious perception. Language therefore seems to play an active role in perception and helps to optimize it in the long run.

Authors' contributions

Both authors developed the study design, discussed the results and wrote the manuscript. M.M. rendered the stimuli and performed data collection and analyses.

Acknowledgments

We thank C. Braun, A. Enge, K. Stark, and P. Weller for supporting data collection, Z. Kalogeropoulou and V. Chirkov for advice on Greek and Russian task instructions, and G. Kiecker for technical support.

References

Athanasopoulos, P. (2009). Cognitive representation of colour in bilinguals: The case of Greek blues. *Bilingualism: language and cognition, 12*(01), 83-95. doi:10.1017/S136672890800388X

Athanasopoulos, P., Dering, B., Wiggett, A., Kuipers, J.-R., & Thierry, G. (2010). Perceptual shift in bilingualism: Brain potentials reveal plasticity in pre-attentive colour perception. *Cognition, 116*(3), 437-443. doi:http://dx.doi.org/10.1016/j.cognition.2010.05.016

Baayen, R. H., Davidson, D. J., & Bates, D. M. (2008). Mixed-effects modeling with crossed random effects for subjects and items. *Journal of memory and language, 59*(4), 390-412.

Bates, D., Mächler, M., Bolker, B., & Walker, S. (2014). Fitting linear mixed-effects models using lme4. *Journal of Statistical Software, 67*(1), 1-48. doi:doi:10.18637/jss.v067.i01

Brown, A. M., Lindsey, D. T., & Guckes, K. M. (2011). Color names, color categories, and color-cued visual search: Sometimes, color perception is not categorical. *Journal of Vision, 11*(12), 2. doi:10.1167/11.12.2

Chua, F. (2005). The effect of target contrast on the attentional blink. *Perception and Psychophysics, 67*(5), 770-788. doi:10.3758/BF03193532

Cukur, T., Nishimoto, S., Huth, A. G., & Gallant, J. L. (2013). Attention during natural vision warps semantic representation across the human brain. *Nature Neuroscience, 16*(6), 763-770. doi:Doi 10.1038/Nn.3381

Delorme, A., & Makeig, S. (2004). EEGLAB: an open source toolbox for analysis of single-trial EEG dynamics including independent component analysis. *Journal of Neuroscience Methods, 134*(1), 9-21.

Di Russo, F., Martinez, A., Sereno, M. I., Pitzalis, S., & Hillyard, S. A. (2002). Cortical sources of the early components of the visual evoked potential. *Human Brain Mapping, 15*(2), 95-111. doi:10.1002/Hbm.10010

Firestone, C., & Scholl, B. J. (2015). Cognition does not affect perception: Evaluating the evidence for 'top-down'effects. *Behavioral and Brain Sciences, 39*, 1-72.

Forder, L., He, X., & Franklin, A. (2017). Colour categories are reflected in sensory stages of colour perception when stimulus issues are resolved. PloS One, 12(5), 1-16.

Frömer, R., Maier, M., & Abdel Rahman, R. (2018). Group-Level EEG-Processing Pipeline for Flexible Single Trial-Based Analyses Including Linear Mixed Models. *Frontiers in Neuroscience, 12*(48), 1-15. doi:10.3389/fnins.2018.00048

Gilbert, A. L., Regier, T., Kay, P., & Ivry, R. B. (2006). Whorf hypothesis is supported in the right visual field but not the left. *Proceedings of the National Academy of Sciences of the United States of America, 103*(2), 489-494. doi:10.1073/pnas.0509868103

Gilbert, C. D., & Li, W. (2013). Top-down influences on visual processing. *Nature Reviews: Neuroscience, 14*(5), 350-363. doi:10.1038/Nrn3476

Goldstone, R. L., & Hendrickson, A. T. (2010). Categorical perception. *Wiley Interdisciplinary Reviews: Cognitive Science, 1*(1), 69-78. doi:10.1002/Wcs.26

Green, P., & MacLeod, C. J. (2016). SIMR: an R package for power analysis of generalized linear mixed models by simulation. *Methods in Ecology and Evolution, 7*(4), 493-498. doi:10.1111/2041-210X.12504

Hohenstein, S., & Kliegl, R. (2015). remef: Remove Partial Effects. R package version 1.0.6.9000. Retrieved from https://github.com/hohenstein/remef/

Ille, N., Berg, P., & Scherg, M. (2002). Artifact correction of the ongoing EEG using spatial filters based on artifact and brain signal topographies. *Journal of Clinical Neurophysiology, 19*(2), 113-124.

Ishihara, S. (2014). *Ishihara's Tests for Colour Deficiency: 24 Plates*. Tokyo: Kanehara Trading Inc.

Itti, L., & Koch, C. (2001). Computational modelling of visual attention. *Nature Reviews: Neuroscience, 2*(3), 194-203.

Kuznetsova, A., Brockhoff, P. B., & Christensen, R. H. B. (2016). lmerTest: Tests in Linear Mixed Effects Models. R package version 2.0-33. Retrieved from http://CRAN.R-project.org/package=lmerTest

Lupyan, G. (2012). Linguistically modulated perception and cognition: the label-feedback hypothesis. *Frontiers in Psychology, 3*, 54. doi:10.3389/fpsyg.2012.00054

Lupyan, G., & Ward, E. J. (2013). Language can boost otherwise unseen objects into visual awareness. *Proceedings of the National Academy of Sciences of the United States of America, 110*(35), 14196-14201. doi:10.1073/pnas.1303312110

Maier, M., Glage, P., Hohlfeld, A., & Rahman, R. A. (2014). Does the semantic content of verbal categories influence categorical perception? An ERP study. *Brain and Cognition, 91*, 1-10. doi:DOI 10.1016/j.bandc.2014.07.008

Marian, V., Blumenfeld, H. K., & Kaushanskaya, M. (2007). The Language Experience and Proficiency Questionnaire (LEAP-Q): Assessing Language Profiles in Bilinguals and Multilinguals. *Journal of Speech, Language, and Hearing Research, 50*(4), 940-967. doi:10.1044/1092-4388(2007/067)

Martens, S., & Wyble, B. (2010). The attentional blink: Past, present, and future of a blind spot in perceptual awareness. *Neuroscience and Biobehavioral Reviews, 34*(6), 947-957. doi:http://dx.doi.org/10.1016/j.neubiorev.2009.12.005

R Core Team. (2014). R: A language and environment for statistical computing. Vienna, Austria: R Foundation for Statistical Computing.

Raymond, J. E., Shapiro, K. L., & Arnell, K. M. (1992). Temporary suppression of visual processing in an RSVP task: An attentional blink? *Journal of Experimental Psychology: Human Perception and Performance, 18*(3), 849-860. doi:10.1037/0096-1523.18.3.849

Regier, T., & Kay, P. (2009). Language, thought, and color: Whorf was half right. *Trends in Cognitive Sciences, 13*(10), 439-446. doi:10.1016/j.tics.2009.07.001

Roberson, D., Pak, H., & Hanley, J. R. (2008). Categorical perception of colour in the left and right visual field is verbally mediated: Evidence from Korean. *Cognition, 107*(2), 752-762. doi:10.1016/j.cognition.2007.09.001

Sergent, C., Baillet, S., & Dehaene, S. (2005). Timing of the brain events underlying access to consciousness during the attentional blink. *Nature Neuroscience, 8*(10), 1391-1400. doi:http://www.nature.com/neuro/journal/v8/n10/suppinfo/nn1549_S1.html

Shapiro, K. L., Caldwell, J., & Sorensen, R. E. (1997). Personal names and the attentional blink: A visual "cocktail party" effect. *Journal of Experimental Psychology: Human Perception and Performance, 23*(2), 504-514. doi:10.1037/0096-1523.23.2.504

Thierry, G., Athanasopoulos, P., Wiggett, A., Dering, B., & Kuipers, J. R. (2009). Unconscious effects of language-specific terminology on preattentive color perception. *Proceedings of the National Academy of Sciences of the United States of America, 106*(11), 4567-4570. doi:10.1073/pnas.0811155106

Vogel, E. K., Luck, S. J., & Shapiro, K. L. (1998). Electrophysiological evidence for a postperceptual locus of suppression during the attentional blink. *Journal of Experimental Psychology: Human Perception and Performance, 24*(6), 1656-1674. doi:10.1037/0096-1523.24.6.1656

Winawer, J., Witthoft, N., Frank, M. C., Wu, L., Wade, A. R., & Boroditsky, L. (2007). Russian blues reveal effects of language on color discrimination. *Proceedings of the National Academy of Sciences of the United States of America, 104*(19), 7780-7785. doi:10.1073/pnas.0701644104

Wolff, P., & Holmes, K. J. (2011). Linguistic relativity. *Wiley Interdisciplinary Reviews: Cognitive Science, 2*(3), 253-265. doi:10.1002/Wcs.104