Research on social influence has a long tradition of using perceptual decision-making tasks to examine how the opinions of others change individuals’ judgments. Yet, the specific cognitive mechanisms mediating such changes are not well understood. In particular, the question remains largely unanswered of whether social influence affects the uptake of basic sensory information (i.e., a perceptual bias) or whether it alters the decision criteria (i.e., a judgmental bias) or both. Using a diffusion model approach, our study is the first to disentangle these two mechanisms in social influence.

Classic Studies on Social Influence

Sherif (1935) investigated the emergence of social norms. In a dark room he asked participants to judge the movement of a small spot of light. In reality, the light spot was stationary and only appeared to move (autokinetic effect). When the participants judged the extent of movement of the spot of light in groups, their estimates successively converged over several trials to the mean of the group. Subsequently, the established norms strongly influenced individuals’ judgments outside of the group context. Hence, Sherif showed that norms can shape individual decisions even in the absence of an immediate social context. This finding, however, raised two questions: First, because of the ambiguity of the stimulus, it remains unclear whether social influence can affect decisions about unambiguous visual information. Second, the cognitive mechanisms underlying social influence were not investigated: Did the social norm bias the perception of movement or did it bias the judgment by changing the criterion on which participants based their judgments?

The first question was addressed by the seminal experiments of Asch (1956). He presented a single vertical line on one chart and three vertical lines on another. During several trials, participants had to decide which of the three lines had the same length as the single line. In a control condition, in which participants gave their responses alone, the error rate was 0.7%. Hence, the correct answer was clearly identifiable. Participants were confronted with a unanimously wrong majority of five to seven confederates before they had to judge the stimulus themselves. Intriguingly, participants went along with the incorrect majority in 37% of the trials. In the following decades, many studies replicated this finding under varying conditions (for reviews, see Bond, 2005; Bond & Smith, 1996). But why do people conform?

Abstract

Classic studies on social influence used simple perceptual decision-making tasks to examine how the opinions of others change individuals’ judgments. Since then, one of the most fundamental questions in social psychology has been whether social influence can alter basic perceptual processes. To address this issue, we used a diffusion model analysis. Diffusion models provide a stochastic approach for separating the cognitive processes underlying speeded binary decisions. Following this approach, our study is the first to disentangle whether social influence on decision making is due to altering the uptake of available sensory information or due to shifting the decision criteria. In two experiments, we found consistent evidence for the idea that social influence alters the uptake of available sensory evidence. By contrast, participants did not adjust their decision criteria.

Keywords

conformity, social influence, perceptual decision-making, diffusion model, motivated reasoning

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Research on social influence has a long tradition of using perceptual decision-making tasks to examine how the opinions of others change individuals’ judgments. Yet, the specific cognitive mechanisms mediating such changes are not well understood. In particular, the question remains largely unanswered of whether social influence affects the uptake of basic sensory information (i.e., a perceptual bias) or whether it alters the decision criteria (i.e., a judgmental bias) or both. Using a diffusion model approach, our study is the first to disentangle these two mechanisms in social influence.

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To answer this question, previous studies have focused on motivational and goal-related explanations (e.g., informational vs. normative influence; Deutsch & Gerard, 1955) as well as on moderating variables (e.g., group size or self-esteem; Bond, 2005; Cialdini & Goldstein, 2004). By contrast, few studies have addressed the second question raised by Sherif’s results (1935): Do people adjust their decision criteria in favor of the majority response so that less evidence is needed to adopt the source’s opinion? Or does social influence bias the uptake of available information? To our interest, when participants of the Asch experiments were asked why they went along with the majority, at least some of them insisted that they had actually seen the line lengths as they had reported, thereby providing anecdotal evidence for the idea that a majority response might indeed induce a change in perceptual processes.

Building on the idea that social influence is able to induce a change in perception, Moscovici and Personnaz (1980) postulated that a minority is likely to exert its effect by altering the underlying perceptual processes themselves, whereas majority influence yields only verbal compliance. Using an afterimage paradigm, Moscovici and Personnaz (1980) found support for this hypothesis. However, other authors failed to replicate these findings (e.g., Martin, 1998; Sorrentino, King, & Leo, 1980). Particularly, the findings of Martin (1998) suggest that the afterimage results might be an artifact. Thus, it remains unclear whether any source of social influence—minority and majority—can actually bias perception. Moreover, the alternative hypothesis that individuals adjust their decision criteria in favor of a majority or minority response has not been addressed directly by this research either.

Recent Research on the Neural Mechanisms Underlying Social Influence

Recently, a growing number of neuroimaging studies has sought to provide new insights into the cognitive mechanism underlying social influence (e.g., Berns et al., 2005; Falk, Berkman, Mann, Harrison, & Lieberman, 2010; Klucharev, Munneke, Smidts, & Fernández, 2011). The present reviews of Falk, Way, and Jasinska (2012) and Izuma (2013) suggest that this emerging body of evidence can be integrated in a reinforcement learning framework. In particular, Falk et al. (2012) argue that normative social influence is mediated by neural systems sensitive to social rewards and punishments. This is consistent with studies showing that conformity and responsiveness to social norms are typically associated with activity in areas of the brain’s reward system (e.g., ventral striatum, ventromedial prefrontal cortex). These studies suggest that social influence biases decision making by social reinforcement values assigned to choice options. However, they do not address the question of how these reinforcement values influence the decision-making process itself: Do they change the decision criteria so that less supportive information is needed to take the option with the highest social reinforcement value? Or do they change the information uptake so that processing of sensory information is biased toward the option with the highest social reinforcement value?

Two exceptions are the studies of Zaki, Schirmer, and Mitchell (2011) and Berns et al. (2005). Zaki et al. asked participants to rate the attractiveness of faces. After having learned how their peers allegedly rated each face, participants were scanned using fMRI while they again rated each face. Zaki et al. found that when social influence affected ratings, this was accompanied by modulated engagement of brain areas associated with coding subjective value (nucleus accumbens and orbitofrontal cortex), and concluded that social influence modifies the value assigned to a stimulus. However, based on these data, one cannot conclude whether the peer ratings (i.e., the social reinforcement value) induced a biased uptake of the information which, in turn, altered the value of the face itself or whether it induced a shift in the decision criteria.

Berns et al. (2005) used a mental rotation task and found that when participants went along with a majority response, activity increased in the neural network that is implicated in mental rotation (i.e., the occipital–parietal network). They interpreted this result as evidence for social influence affecting perceptual processes. However, two arguments can be raised against this conclusion: First, we cannot be sure that the activity in the occipital–parietal network observed when participants went along with the majority is indeed causally involved in social influence. Second, because of the lack of spatial and temporal resolution of the fMRI signals, the activity in this network may not necessarily reflect perceptual processing changes in the occipital cortex, but may be related to the decision itself, which is represented in parietal areas (cf. Gold & Shadlen, 2007; Možiš and Krug, 2008).

Again, a possible perceptual bias (i.e., biased information uptake) cannot be separated from a possible judgmental bias (i.e., biased decision criteria).

In sum, the neuroscientific evidence suggests that the motivational forces behind social influence are mediated by the brain’s reward system. Furthermore, there is tentative evidence that social influence can possibly alter decisions by biasing the processing of available sensory information. However, as yet, no neuroimaging study has been able to assess and compare the specific contribution of perceptual and judgmental biases to the behavioral effect of social influence. Thus, even if we hypothetically assume that fMRI studies provide evidence for the idea that social influence alters perceptual processes, these studies cannot rule out the possibility that judgmental biases also contribute to the effects observed.

In the following, we will introduce the diffusion decision model, and explain how this model can be used to characterize the contribution of different cognitive processes to social influence effects.
The Diffusion Decision Model

Research on perceptual decision making has long sought to establish if perceptual decisions are driven by a judgmental bias (i.e., a change in decision criteria) or by a perceptual bias (i.e., a change in information uptake). The diffusion decision model (Ratcliff, 1978; Ratcliff & McKoon, 2008) represents a well-established method in research on perceptual decision making to separate these processes in speeded binary decision tasks (e.g., Heekeren, Marrett, Bandettini, & Ungerleider, 2004; Voss, Rothermund, & Brandstädter, 2008).

For illustration of the basic model rationale, imagine a dermatologist who has to decide whether a mole or patch of skin is either cancerous (Decision “A”) or not (Decision “B”). According to the model, the visual information about the condition of the skin is sequentially accumulated over time. This perceptual process is mathematically represented by an internal counter starting with the value of \( z \) (see Figure 1 for a graphical representation of the model). Evidence supporting one decision (decision “A”) increases the value of the counter, whereas information supporting the other decision (decision “B”) decreases its value. To reach a decision, the value of the counter has to exceed either the upper threshold for decision “A” or the lower threshold for decision “B” (0). The accumulation process terminates as soon as the upper or the lower threshold is reached. The distance between thresholds (0 and \( a \), that is, the value of \( a \)) thereby represents the general amount of information needed to reach a decision. For instance, if the spot is a noncancerous mole, the dermatologist will be likely to accumulate more sensory information indicating normal skin (e.g., color and form), thereby reaching his criterion for the decision “B” (i.e., “noncancerous”).

The process of accumulating sensory evidence is assumed to be noisy (i.e., influenced by random effects). Therefore, it is described by a stochastic diffusion process consisting of a systematic and a random component. The systematic component, called the drift rate (\( v \)), represents the average amount of evidence accumulated per time unit. Thus, the drift rate is a measure of how fast sensory information accumulates in the decision process. Positive values indicate that more evidence for decision “A” relative to decision “B” is accumulated, whereas negative values indicate that more evidence supporting “B” is gathered. The random component is Gaussian noise, which is added to this constant drift. This can lead to different pathways of the accumulation process even when the drift rate is the same. For example, if the dermatologist examined the same spot several times, random influences would lead to different decision times or even to different decisions depending on how strong the constant drift in the accumulation process is. Consistent with this idea, it was shown that the drift rate mainly depends on the physical characteristics of a stimulus (i.e., how clear it indicates the correct decision; Voss, Rothermund, & Voss, 2004) as well as psychological influences on stimulus processing (i.e., biased information uptake; Voss et al., 2008). In addition, the duration of nondecisional processes (e.g., motoric response processes) is mapped by the response-time constant (\( t_f \)).

According to the diffusion decision model, prior knowledge can influence the decision process in two possible ways: (a) prior knowledge affects the rate of information uptake (i.e., the drift rate, \( v \)) and/or (b) it leads to a shift in the starting point of the accumulation process (\( z \)). The diffusion model can be used to disentangle these two mechanisms.

The first scenario (i.e., a change in the drift rate \( v \)) indicates a perceptual bias. For example, if colleagues of the dermatologist have diagnosed the spot as cancerous (decision “A”), it is likely that information supporting this decision will be accumulated faster than information indicating that the spot is noncancerous (decision “B”). In other words, a change in the drift rate indicates that the process of accumulating sensory evidence is biased in favor of one decision alternative. By contrast, the second scenario describes a judgmental bias, which is unrelated to perceptual processes. In terms of the diffusion model, judgmental biases are reflected by an asymmetric setting of thresholds with regard to the amount of information required to terminate information uptake (i.e., a shift in the starting point \( z \)). For example, learning about her colleagues’ diagnosis might lead the dermatologist to change her decision criterion accordingly without biasing how she accumulates the sensory information. In this case, the starting point \( z \) will shift in the direction of the threshold for decision “A.” Hence, less supportive information is needed to reach threshold “A” without affecting the way sensory evidence is processed.

In a prototypical study using a diffusion model analysis, participants have to complete a speeded binary decision task consisting of a number of trials in each condition. Then, for each single participant the resulting empirical shape of response time distributions for decision “A” and
decision “B,” as well as the proportions of both responses in each condition are simultaneously used to estimate the parameter values for each condition. Thus, in a diffusion model analysis, data from each individual participant are modeled separately. More specifically, a diffusion model analysis involves a multidimensional search for the parameter values until the predicted response time distributions optimally fit the empirical response time distributions. In the end, the individual estimated parameter values of all participants can then be used in statistical analysis to test for differences between experimental conditions (see Voss, Nagler, & Lerche, 2013, for a tutorial in diffusion modeling). Differences in parameter values between conditions can then be interpreted as differences in the underlying decision process, which is represented by the correspondent parameter. For instance, in our study, we estimated the values for drift rate and starting point to test whether they were altered by the experimentally induced social influence (for details of the diffusion analysis, see also Results). Thus, we could disentangle if social influence on perceptual decision making is due to a perceptual bias (i.e., a change in drift rate) and/or due to a judgmental bias (i.e., a change in starting point).

In sum, in contrast to more conventional forms of analyses treating response times and response rates separately (e.g., calculation of mean values, signal detection analysis), a major advantage of a diffusion model analysis is that it simultaneously takes all behavioral data into account to provide an insight into the underlying decision processes.

Surprisingly, so far the diffusion model has not been used to examine the cognitive mechanisms underlying social influence. The present research aims to fill this void.

The Present Research

In the present research, we aimed to examine whether effects of social influence on perceptual decision making are due to (a) a perceptual bias (i.e., a bias in information uptake), (b) an asymmetry in the decision criteria (i.e., a judgmental bias), or both. To this end, we used a diffusion model analysis to test whether a majority exerts its influences through changes in the drift rate, indicating a perceptual bias, and/or changes in the starting point, indicating a judgmental bias.

In each experimental session, four participants (sitting in the same room) had to complete a perceptual decision-making task simultaneously on separate computers. On multiple trials, they had to decide as quickly and as accurately as possible whether the dominant color of a square was orange or blue. The squares consisted of randomly ordered blue and orange pixels. To manipulate task difficulty, the proportion of pixels in each color was varied. To induce social influence, the alleged responses of the other three participants were presented on the screen before the stimulus was shown. In fact, everything was preprogrammed, and the other participants’ responses were experimentally varied resulting in unanimous majority responses which were either correct or incorrect. By presenting the majority response prior to the visual stimuli, we were able to conduct a diffusion model analysis of the response time distributions triggered by the stimuli (Ratcliff & McKoon, 2008).

Since the majority responses were always displayed prior to presenting the visual stimulus, it is conceivable that the majority responses could also have a priming effect on individual responses. Thus, if participants follow the majority, this could be due to social influence and priming. To disentangle these two processes, we used a control condition in which participants were told that, on a given trial, each participant would respond to a different visual stimulus. Hence, the other participants’ responses would be irrelevant for their own responses. By contrast, in the experimental condition, participants were told that, on each trial, they were all presented with the same stimulus and, therefore, the other participants’ responses would be relevant for them. If the majority responses in the control condition have any effect on the participants’ responses, this would be due to priming effects. Consequently, any difference between the experimental and control condition can be attributed to social influence.

We predict that majority influence will have a stronger effect in the experimental condition than in the control condition. In addition, we predict that majority influence will affect information uptake and decision criteria. With regard to the diffusion model analysis, we hypothesize that effects of social influence will be accompanied by changes in the drift rate and changes in the starting point. The predicted effects should be reflected in significant two-way interactions between majority relevance (i.e., control vs. experimental condition) and majority response. Thus, for each dependent variable, we expect larger effects of the majority response in the experimental condition compared with that of the control condition.

Experiment I

Method

Participants and design. Fifty-nine students (46 female, average age = 22.8 years) were randomly assigned to the two conditions of majority relevance: In one condition, majority responses were relevant (R+ Condition) for the participants’ own responses, because participants thought they referred to the same stimulus. In the other condition, they were not relevant (R− Condition, see Procedure for details), because participants had been told that the responses referred to a different stimulus. Female and male participants were approximately evenly distributed across conditions. The study was approved by the local ethics committee.

The 2 × 2 × 5 design consisted of the between-subjects factor majority relevance (R+ vs. R−) and the two within-subjects factors majority response (orange vs. blue) and
orange proportion in the stimulus (48%, 49%, 50%, 51%, 52%, see Figure 2A). The assignment of colors to response keys (orange left vs. right) was counterbalanced between participants.

Stimuli. The stimuli were adapted from Voss et al. (2008). Squares of 128 × 128 orange and blue pixels were presented at a resolution of 512 × 512 screen pixels. For each trial, the positions of pixels were randomized. Furthermore, one of five levels of orange proportion was randomly selected for each trial by coloring the corresponding number of pixels orange and the remaining pixels blue. In a pretest \((n = 41)\), we found that the five levels of the orange proportion could be clearly discriminated from each other; all \(t_s > 7.63\), all \(p_s < .001\). The mean relative rate of orange responses for the five levels of orange proportion in ascending order were 0.18 \((SD = 0.18)\), 0.31 \((SD = 0.19)\), 0.49 \((SD = 0.21)\), 0.66 \((SD = 0.17)\), and 0.80 \((SD = 0.15)\). The experiment was run with PsychoPy-2 (Peirce, 2007, 2009).

Procedure. Four participants of the same gender were invited to each experimental session. If a participant did not show up, he or she was replaced with a confederate so that the session could take place. Since the majority responses were preprogrammed, the confederates had no experimental function.

On arrival, participants signed informed-consent forms and were led to the computer lab where they were seated at their respective computers. Participants were separated by dividing walls that restricted any eye contact and social interaction with each other. They were instructed not to speak with each other during the experimental session. In addition, participants wore headphones to avoid hearing each other’s button presses.

Participants were told that they would take part in a computer-based study on color perception. During each trial, they would have to decide individually as quickly and as accurately as possible whether a visual stimulus was dominated by the color orange or blue. In addition, participants

Figure 2. A. An example of stimulus and majority responses (dark grey = blue, light grey = orange); B. Temporal sequence of a trial. Timings are given in milliseconds.
Note. Silhouettes would be replaced with photographs in the experiment, the grey photograph would show the participant.
were told that their individual computers were connected via a server, which was running the task. In reality, all participants completed the task individually on stand-alone computers.

Moreover, participants were told that there was a specific order in which they would have to respond in each trial. At the beginning of the experiment, the server would randomly determine this order. Importantly, every participant was then instructed that he or she had been randomly chosen to respond last in each trial. The alleged order of responses was visualized in a series of small portrait photos of all participants at the bottom of each of their computer screens (see Figure 2A). These photos had been taken and uploaded by the experimenter at the beginning of the session. Participants were told that each participant’s response for the present trial would be displayed above each portrait, in the sequence in which the responses were made (i.e., above each photo the word “orange” or “blue” was displayed). In reality, the displayed responses on each trial were not actual responses of the other participants, but generated by the experimental software. Thus, during each trial, each participant initially saw the alleged responses of the three other participants before they were presented with the visual stimulus, and had to make their own response, which was then displayed on the screen (see Figure 2B).

To simulate realistic behavioral responses, each alleged response of another participant appeared after a random delay of between 1,100 and 1,900 ms. 500 ms after the third response, a white fixation cross was shown for 500 ms at the center of the stimulus field. Then the stimulus was presented for a maximum of 1,500 ms During this time, participants had to give their response, which terminated the stimulus presentation. At the end of each trial, all four portraits and associated responses, including the participant’s actual response, were presented for 1,000 ms. After a black screen was presented for 500 ms, the next trial began. The trial length varied between 7,300 and 9,700 ms.

Each participant carried out 200 experimental trials (20 trials for every combination of the two within factors). During one half of these trials, the other three participants allegedly unanimously responded with “orange,” and during the other half of the trials they allegedly unanimously responded with “blue.” To maintain the credibility of the other participants’ responses, filler trials were added in which either the other participants gave nonunanimous responses (60 trials) or one of the participants failed to give an answer (8 trials). Hence, overall, 268 trials had to be completed. The different types of experimental and filler trials were evenly distributed across four blocks. There was a practice block of 20 trials before the four blocks, and there were breaks of 1 min between the blocks.

To control for priming effects, we manipulated majority relevance between participants. Participants in the R+ Condition were told that, in each trial, all four of them would respond to the same stimulus. In contrast, participants of the R− Condition were told that each of them would respond to a different stimulus in each trial. As a rationale for why they were exposed to the other participants’ responses, participants in the R− Condition were told that the other responses would only serve as a cue to let them know when it would be their turn to respond. Thus, the only difference between the two stimulus conditions was the relevance of the behavioral responses. Therefore, if we observe stronger majority effects in the R+ than in the R− Condition, these differences should be due to genuine effects of social influence and not priming.

After the last trial, participants were thanked, probed for suspicion, and debriefed.

Results

Suspicion check and preliminary analyses. Nine participants (four in the R+ Condition, and five in the R− Condition) had to be excluded from further analyses, because they voiced suspicions that the responses of the other participants were manipulated and, hence, not authentic. Therefore, all analyses reported in the following are based on a sample of 50 participants (24 in the R− Condition, 26 in the R+ Condition).

Participants were then divided into two subgroups: Participants in the first subgroup (31 participants) had noted in the suspicion check that feedback on the responses was given to influence their decisions, whereas participants of the second subgroup (19 participants) did not express this suspicion. The two subgroups were evenly distributed over the R+ and R− conditions, χ2 (1, n = 50) = 0.005, p = .944. Note that participants in both subgroups did not question the authenticity of the majority responses. To check for differences between these subgroups, we entered subgroup as an additional factor in our experimental design. The results showed that there were neither significant main effects nor significant interaction effects for this factor, all ps > .14. Hence, this factor was subsequently dropped from the analyses reported in the following.

Response probabilities. As a dependent variable, we used the relative rate of orange responses (see Figure 3). Responses slower than 1,500 ms were excluded (1.83%). A 2 (majority relevance: R+ vs. R−) × 2 (majority response: orange vs. blue) × 5 (orange proportion: 48% vs. 49% vs. 50% vs. 51% vs. 52%) ANOVA with repeated measures on the last two factors revealed a significant main effect for majority response, F(1, 48) = 46.73, p < .001, ηp² = .49. Participants gave more orange responses when confronted with an orange (M = 0.57, SD = 0.18) than with a blue majority response (M = 0.35, SD = 0.14).†

The predicted two-way interaction of majority response and majority relevance reached significance, F(1, 48) = 30.38, p < .001, ηp² = .30. To examine this interaction more closely, we conducted separate simple ANOVAs for the R+
and the R− Condition. In both conditions, the effect of majority response was significant, all $F$s > 5.21, all $p$s < .032. Hence, majority responses changed participants’ behavior in both conditions. However, the majority effects were stronger in the R+ than in the R− condition: In the R− condition the relative rate of orange responses was 0.41 ($SD = 0.14$) versus 0.48 ($SD = 0.13$) when the majority response was blue versus orange, respectively. By contrast, in the R+ condition the relative rate of orange responses was 0.30 ($SD = 0.13$) versus 0.65 ($SD = 0.18$) when the majority response was blue versus orange, respectively. These analyses show that the effects of a unanimous majority on perceptual decision-making were not just induced by priming, but were due to social influence.

**Diffusion model analysis.** To analyze whether the effects of social influence shown hereinbefore are based on changes in perceptual processing, decision criteria, or both, we conducted a diffusion model analysis with the program *fast-dm* (Voss & Voss, 2007).

Following Voss et al. (2008), the model’s parameters were estimated separately for each participant. The upper decision threshold always corresponded to the orange response and the lower decision threshold to the blue response. For the two majority responses, different starting points ($z$) were allowed to map possible changes in the decision criteria (i.e., the judgmental bias). Moreover, for each majority response on each level of the orange proportion, different drift rates ($\nu$) were allowed to analyze whether majority responses lead to changes in perceptual processing. Positive versus negative values of the drift rate indicate that relatively more information is accumulated for an “orange” (the upper threshold) versus a “blue” response (lower threshold). The response-time constant ($t_0$) and the distance between thresholds ($a$) were held constant across all conditions. For the sake of parsimony, intertrial variability parameters were assumed to be zero. Thus, the model comprised 14 parameters (2 starting points, 10 drift rate, 1 threshold separation and 1 response-time constant).

**Model fit.** We first assessed the model fit by using the combined probability values of the Kolmogorov–Smirnov (KS) statistic (Voss & Voss, 2007). The KS statistic compares the empirical with the predicted distribution functions of response frequency and response times for each participant in each condition. *Fast-dm* reports combined $p$ values that result from the multiplication of the single $p$ values from the 10 different conditions. The mean of the combined $p$ values was .37 ($SD = .20$). These $p$ values are difficult to interpret because, on one hand, they might be notably smaller than the typical convenient alpha level of .05, because multiple models are tested simultaneously. On the other hand, the KS test is biased when a function is fitted to data, resulting in increased $p$ values. To overcome these problems we ran a simulation study on model fit. For this purpose, we generated 1,000 parameter sets, for which parameter values were randomly chosen from a multivariate normal distribution defined by the empirical parameter values. For each of

![Figure 3. Proportion of orange responses and standard errors as a function of orange proportion (x-axis), relevance condition (R+ = belted vs. R− = nonbelted) and majority response (MRO = orange in light grey vs. MRB = blue in dark grey).](image-url)
these parameter sets, a random data set was simulated using the construct-samples routine from fast-dm, and parameters were reestimated from the simulated data sets. This gave us a distribution of fit indices for data based on a diffusion process as assumed by the model. The 5% quantile of this distribution defined a critical value to reject a model. Results show that models with a combined p value of p < .005 have to be rejected. None of the empirical models had a poor fit according to this criterion.

Relative starting point. As noted hereinbefore, the relative starting point can be used to determine whether the participants change their decision criteria dependent on the majority response. In line with Voss et al. (2008), we calculated the relative starting point as z divided by a (z/a = 0.5 indicates a starting point located in the midpoint between the thresholds). A 2 (majority relevance) × 2 (majority response) ANOVA with the relative starting point as a dependent variable did not reveal any significant main effect or interaction, all Fs < 1.17, all ps > .286 (see Table 1).

Drift rates. To test whether social influence effects were due to a perceptual bias, the estimated drift rates were entered in a 2 (majority relevance) × 2 (majority response) × 5 (orange proportion) ANOVA (see Table 1 and Figure 4). The main effect for majority relevance was significant, F(1, 48) = 40.97, p < .001, η² = .46, showing overall higher drift rates for orange (M = 0.28, SD = 0.79) than for blue majority responses (M = −0.61, SD = 0.63). In addition, the predicted two-way interaction of majority relevance and majority response was significant, F(1, 48) = 12.84, p = .001, η² = .21.

To disentangle this interaction, we conducted separate simple ANOVAs for the R+ and the R− Condition. In both conditions, the effect of majority relevance was significant, all Fs > 5.56, all ps < .027. Thus, the majority response affected the drift rate in both conditions, but this effect was by far larger in the R+ Condition than in the R− Condition.

Table 1. Results of the Diffusion Model Analysis, Experiment 1.

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<tr>
<th>Parameter</th>
<th>MRB</th>
<th>MRO</th>
<th>MRB</th>
<th>MRO</th>
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</tr>
<tr>
<td>t0</td>
<td>0.61 (0.10)</td>
<td>0.63 (0.13)</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note. Mean values (and standard deviations) for all parameters. R− = non relevant majority response, R+ = relevant majority response, MRB = blue majority response, MRO = orange majority response, v = drift rate, z/a = relative starting point. Note that distance between the decision thresholds a and response-time constant t0 did not vary across the within conditions.

The R− Condition showed only slightly higher mean drift rates for orange (M = −0.04, SD = 0.74) than for blue majority responses (M = −0.42, SD = 0.63). In contrast, the R+ Condition showed markedly higher mean drift rates for orange (M = 0.57, SD = 0.73) than for blue majority responses (M = −0.79, SD = 0.58).

Other parameters. To test whether there were any significant differences in the remaining parameters of the diffusion model (a, t0) between conditions R+ and R−, several t tests were run (see Table 1). In the R+ Condition, the distance between the decision thresholds (a) was significantly larger (M = 1.40, SD = 0.17) than in the R− Condition (M = 1.31, SD = 0.14); t(48) = 2.03, p = .048. There was no difference between the conditions for the response-time constant (t0), t(48) = 0.61, p = .546.

Discussion

We hypothesized that the majority would have a larger influence on perceptual decision making in the experimental condition (R+) than in the control condition (R−). As predicted, participants in the R+ Condition adopted the majority response more often than those in the R− Condition regardless of its correctness. In addition, the diffusion model analysis indicated that social influence was due to a change in drift rate, which was larger in condition R+ than in condition R−. In other words, sensory information supporting the majority response was processed more efficiently than sensory information contradicting the majority response. By contrast, the starting point was not affected by the majority responses. Hence, social influence in this experiment can be explained by a perceptual bias but not by a judgmental bias. To the best of our knowledge, this is the first clear evidence that social influence effects are due to a bias in perceptual processes of information uptake.

Similar to the study by Sherif (1935), a limitation of our results might be that participants had to judge a set of relatively ambiguous stimuli. Hence, we cannot be certain whether the perceptual bias that we found in Experiment 1 is strong enough to explain social influence effects in cases where stimuli are unambiguous. Therefore, we conducted a second experiment with the same paradigm, but this time using unambiguous stimuli.

Experiment 2

Method

Participants and design. Thirty-five female students (average age = 22.3 years) were randomly assigned to the experimental conditions of a 2 × 2 × 3 design with majority relevance (R+ vs. R−) as a between-subject factor, and majority response (orange vs. blue) and proportion of orange pixels (46% vs. 50% vs. 54%) as within-subject factors. In addition,
the assignment of colors to response keys (orange left vs. right) was counterbalanced across participants.

**Stimuli and procedure.** Stimuli and procedure were the same as in Experiment 1, except that the two extreme stimulus levels were perceptually unambiguous in their pixel proportions (46%, 50%, 54%, compared with 48%, 49%, 50%, 51%, 52% in Experiment 1). There were 240 experimental trials (40 trials for every combination of the two within factors), which were equally distributed across the four blocks.

A pretest \((n = 41)\) showed that the mean rate of orange responses for orange proportions of 46% and 54% were 0.08 \((SD = 0.17)\) and 0.93 \((SD = 0.15)\), respectively. In other words, the 46% and 54% stimuli could be correctly identified in over 90% of the trials.

**Results and Discussion**

**Suspicion check and preliminary analyses.** Applying the same exclusion criteria as in Experiment 1, five participants (four in the R+ Condition, one in the R− Condition) had to be excluded. Two participants had to be excluded for technical reasons (one in the R+ Condition, one in the R− Condition). Hence, all analyses reported are based on a sample of 28 participants (15 in the R− Condition, 13 in the R+ Condition).

The suspicion check showed that almost all participants (25 out of 28) thought that one aim of the study was to influence their decisions. However, none of these participants had any suspicion that the majority responses were preprogrammed.

For all following dependent variables, we conducted a \(2 \times 2 \times 3\) ANOVA of the experimental design.

**Response probabilities.** Responses slower than 1,500 ms were excluded (1.38%). The ANOVA with the relative rate of orange responses as the dependent variable yielded a significant main effect for majority relevance, \(F(1, 26) = 10.23, p = .004, \eta^2_p = .28\), showing that participants in the R+ Condition gave more orange responses \((M = 0.51, SD = 0.07)\) than in the R− Condition \((M = 0.44, SD = 0.05)\). As in Experiment 1, the main effect for majority response reached significance, \(F(1, 26) = 40.08, p < .001, \eta^2_p = .61\) (see Figure 5). Thus, participants gave more orange responses when confronted with an orange \((M = 0.61, SD = 0.10)\) than with a blue majority response \((M = 0.37, SD = 0.11)\). Again, as predicted, this main effect was qualified by a significant two-way interaction of majority relevance and majority response, \(F(1, 26) = 26.37, p < .001, \eta^2_p = .50\). This time, the two-way interaction was qualified by a significant three-way interaction, \(F(2, 46) = 10.29, p < .001, \eta^2_p = .28\). To clarify the three-way interaction, we conducted two separate 2 (majority response) × 3 (orange proportion) ANOVAs for the R+ and the R− Condition.

For the R− Condition, the main effect for the orange proportion, \(F(2, 28) = 954.85, p < .001, \eta^2_p = .99\) and the two-way interaction were significant, \(F(2, 28) = 4.40, p = .022, \eta^2_p = .24\). By contrast, the main effect for majority response did not reach the conventional level of significance, \(F(1, 14) = 4.42, p = .054, \eta^2_p = .24\). Simple ANOVAs for each level of orange proportion showed that there was a significant effect.
of majority response for stimuli with a level of 50% orange, \( F(1, 12) = 4.72, p = .047, \eta^2_p = .25 \), but not for the remaining levels, all \( F_s < 4.53 \) and \( p_s > .05 \).

For the R+ Condition, the main effect for orange proportion, \( F(2, 24) = 80.36, p < .001, \eta^2_p = .87 \), and for majority response were significant, \( F(1, 12) = 31.25, p = .001, \eta^2_p = .72 \). Furthermore, the two-way interaction was also significant, \( F(2, 24) = 25.11, p < .001, \eta^2_p = .68 \). In contrast to the R− Condition, for the R+ Condition, simple effects analyses showed significant effects of majority response for all levels of orange proportion; all \( F_s > 9.38 \) and \( p_s < .01 \). The effects of majority response (i.e., the difference in the relative rate of orange responses between blue and orange majority response) were larger in the case of ambiguous 50% stimuli (0.22 vs. 0.83), than in the cases of unambiguous 46% (0.02 vs. 0.28) and 54% (0.71 vs. 0.99) stimuli, respectively (see Figure 5).

In other words, our results revealed social influence effects for the unambiguous 46% and 54% stimuli. By contrast, in the case of ambiguous 50% stimuli, there were effects of priming and social influence.

**Diffusion model analysis.** In line with Experiment 1, different starting points (\( z \)) for each majority response and different drift rates (\( \nu \)) for each level of orange proportion were allowed. The response-time constant (\( t_0 \)) and the distance between thresholds (\( \alpha \)) were held constant across all conditions. Again, intertrial variability parameters were set to zero. Thus, the model comprised 10 parameters (2 starting points, 6 drift rates, 1 threshold separation, and 1 response-time constant).

**Table 2.** Results of the Diffusion Model Analysis, Experiment 2.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>R−</th>
<th>R+</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \alpha )</td>
<td>1.31 (0.23)</td>
<td>1.64 (0.14)</td>
</tr>
<tr>
<td>( z/\alpha )</td>
<td>0.47 (0.08)</td>
<td>0.46 (0.07)</td>
</tr>
<tr>
<td>( \nu_{46%} )</td>
<td>-3.15 (0.88)</td>
<td>-2.73 (0.86)</td>
</tr>
<tr>
<td>( \nu_{50%} )</td>
<td>-0.44 (0.49)</td>
<td>-0.22 (0.52)</td>
</tr>
<tr>
<td>( \nu_{54%} )</td>
<td>2.11 (0.87)</td>
<td>2.47 (0.77)</td>
</tr>
</tbody>
</table>

Note. Mean values (and standard deviations) for all parameters. R− = non relevant majority response, R+ = relevant majority response, MRB = blue majority response, MRO = orange majority response, \( \nu \) = drifte rate, \( z/\alpha \) = relative starting point. Note that distance between the decision thresholds \( \alpha \) and response-time constant \( t_0 \) did not vary across the within conditions.

**Model fit.** The mean of the combined \( p \) values provided by fast-dm was .43 (\( SD = .25 \)). As in Experiment 1, model fit was assessed with a simulation study (\( n = 1,000 \) simulated data sets). The distribution of \( p \) values suggested rejecting models with \( p < .065 \). Following this criterion, the fit from one participant was suspicious (\( p = .039 \)). Thus, the percentage of suspicious models (3.6%) is not larger the expected value of misfits (5%), and overall model fit is assumed to be good.

**Relative starting point.** Using the relative starting point as a dependent variable, the ANOVA yielded no significant effects; all \( F_s < 2.37 \), all \( p_s > .137 \) (see Table 2).

**Drift rates.** Mean drift rates for each condition are displayed in Table 2 and in Figure 6. The ANOVA revealed
significant main effects for majority relevance, \( F(1, 23) = 5.86, p = .023, \eta^2_p = .18 \), and for majority response, \( F(1, 26) = 28.61, p < .001, \eta^2_p = .52 \). The first main effect was due to lower drift rates for the R− Condition (\( M = -0.33, SD = 0.42 \)) than for the R+ Condition (\( M = 0.16, SD = 0.64 \)). The latter effect indicated higher drift rates for orange (\( M = 0.55, SD = 1.19 \)) than for blue (\( M = -0.75, SD = 0.83 \)) majority responses.

More importantly, the two-way interaction of majority relevance and majority response was significant, \( F(2, 52) = 16.43, p < .001, \eta^2_p = .39 \), and qualified by a significant three-way interaction, \( F(2, 52) = 12.66, p = .041, \eta^2_p = .12 \).

To disentangle this interaction, we conducted separate 2 (majority response) × 3 (orange proportion) ANOVAs for the R+ and the R− conditions. For the R− condition, again only the main effect for orange proportion was significant, \( F(2, 28) = 322.42, p < .001, \eta^2_p = .86 \). All other effects did not reach significance, all Fs < 3.60, all ps > .08. In contrast, for the R+ Condition there were significant main effects for orange proportion, \( F(2, 24) = 142.32, p < .001, \eta^2_p = .92 \), and, more importantly, for majority response, \( F(1, 12) = 22.02, p = .001, \eta^2_p = .65 \). The two-way interaction was also significant, \( F(2, 24) = 4.26, p = .026 \). Simple ANOVAs showed significant effects of majority response on each level of orange proportion; all Fs > 15.04, all ps < .002. The effects of majority response (i.e., the difference in drift rate between blue and orange majority response) were larger for 54% stimuli (0.97 vs. 4.08), than in cases of 46% (−3.21 vs. −1.11) and 50% (−0.92 vs. 1.14) stimuli, respectively.

Thus, we replicated the finding that the majority response had a stronger impact on the drift rate in the R+ than in the R− Condition. Actually, there was no effect on the mean drift rate in the R− Condition. In addition, the two-way interaction in condition R+ showed that this effect was enhanced for stimuli with an orange proportion of 54%. We will return to this issue in the “General Discussion” section.

**Other parameters.** As in Experiment 1, the distance between the decision thresholds (\( a \)) was larger for condition R+ (\( M = 1.64, SD = 0.14 \)), than for condition R− (\( M = 1.37, SD = 0.23 \)); \( t(26) = 3.72, p = .001 \). There was no difference between the condition for the response-time constant (\( t_0 \)), \( t(26) = 0.48, p = .638 \) (see Table 2).

**Discussion**

Experiment 2 replicated the results of Experiment 1 with largely disambiguated color stimuli. Even when the stimuli were unambiguous (i.e., in the case of the 46% and 54% stimuli), participants in the experimental condition (R+) adopted the majority response significantly more often than participants in the control condition (R−). Furthermore, the diffusion model analysis demonstrated that this effect was again due to changes in the drift rate. Thus, the results of Experiment 2 suggest that perceptual bias can also account for social influence effects in situations where visual evidence is unambiguous.
General Discussion

Starting with studies by Sherif (1935), Asch (1956) and Moscovici (1980), one of the fundamental questions in social psychology is whether social influence (e.g., norms, majority or minority influence) can alter basic perceptual processes. To address this intriguing issue, we used an experimental paradigm which allowed us to use a diffusion model analysis. Using this model, we tested whether social influence effects on perceptual decision making can be explained by a perceptual bias, a judgmental bias (i.e., an asymmetry in the decision criteria), or by both.

We consistently found that social influence effects were primarily due to a perceptual bias regardless of whether the majority response was correct or incorrect. Since the effects on the drift rate were always stronger in the experimental than in the control condition, we can conclude that the perceptual bias was genuinely caused by social influence (and not by mere response priming effects). Importantly, the results of Experiment 2 show that, even under conditions where the available physical information was in stark contrast to the majority response (e.g., when the orange proportion was 54% and the majority response was “blue”), majority influence was caused by a perceptual bias. Stated differently, even when the stimuli were unambiguous, social influence was due to a bias in the uptake of the sensory information (i.e., a change in the drift rate). In contrast to our expectations, we found no evidence for the idea that social influence is due to a judgmental bias. Thus, participants did not go along with the majority by adjusting their decision criteria. Finally, our results indicate that participants under social influence (i.e., in the experimental condition) appeared to analyze the stimuli more carefully, which was reflected by a larger distance between the decision thresholds (\(a\)) of the diffusion model.

We conclude that a perceptual bias is an important factor in driving social influence on perceptual decision making. However, this does not mean that social influence is never due to a judgmental bias. The question is which contextual factors in our present studies might have diminished the likelihood of a judgmental bias and facilitated the occurrence of a perceptual bias? To answer this, we consider our research in the context of theories and research on motivated reasoning (e.g., Kunda, 1990) and “wishful seeing” (e.g., Balcetis & Dunning, 2010). In this framework, decisions can be driven by accuracy and/or directional goals (i.e., when individuals want to arrive at a particular conclusion; Kunda, 1990). In our task setting, participants were instructed to make correct decisions (goal of accuracy) and might simultaneously be motivated to be part of the majority (directional goal of affiliation).

On one side, an a priori preference to follow the majority irrespective of the given stimulus (i.e., a shift in decision criteria) should be driven by motivational values. In terms of accuracy motivation, the majority response should have no value because participants could learn that it was not a reliable cue to make correct decisions. In terms of affiliation motivation, its value was probably rather weak, because there was no explicit reward or punishment for going along with or against the majority, respectively. For example, although participants’ decisions were identifiable by the majority via the computer screens, participants were not directly confronted with the majority’s reaction to it. Taken together, changing the decision criteria according to the majority response would have only been instrumental to reach the goal of affiliation. However, since such a shift would bear the risk of giving wrong answers and thereby violating the goal of accuracy, it is likely that in our particular study, the majority response did not induce a stable a priori preference. We therefore expect that increasing normative pressure to conform would increase the likelihood of a judgmental bias (e.g., by salient punishments for going against the majority response).

On the other side, the interplay between the goals of accuracy and affiliation could explain the occurrence of a perceptual bias in our studies. As noted by Kunda (1990), motivated reasoning can lead to strong biases in information processing even when accuracy motivation is activated along or in conflict with directional goals. In our task, it was only in trials where majority responses were correct that participants’ goals of accuracy and affiliation could both be fulfilled. If we interpret our results in terms of “wishful seeing” (e.g., Balcetis & Dunning, 2010), it is possible that the perceptual bias that we found in our study was driven by the participants’ wish to see that the majority response is correct, which is the combination of the wish to make a correct decision (i.e., goal of accuracy) and the wish to be a part of the majority (i.e., goal of affiliation), the fulfillment of which represents the optimal outcome. Although these are post hoc interpretations of our results, the suggestions could be examined empirically in future research.

The conflict between the normative and informational value of the majority response could also explain why participants in our study appeared to analyze the stimulus more carefully when exposed to a majority (as reflected by a larger distance between the decision thresholds in the diffusion model analysis). It is interesting to note that the latter finding is in contrast to Moscovici’s (1980) tenet that majorities are influential by inducing compliance without much processing effort. Hence, our results are more in line with the idea that when faced with an incorrect majority, the consensus expectation is broken, which causes people to be surprised. This instigates information-processing activity aimed at understanding the reason for the inconsistency (e.g., Baker & Petty, 1994; Pyszczynski & Greenberg, 1981).

Since we sought to shed light on the cognitive mechanism underlying social influence, we did not address whether the participants in our study were mainly motivated by informational reasons (i.e., the desire to make a
correct decision) or normative reasons (i.e., the desire to be liked by the other group members). Although these motivational orientations are unlikely to completely change the basic cognitive mechanisms underlying social influence, it is conceivable that they have a modulatory function. For example, increasing the need for affiliation by salient social rewards might increase the likelihood that a judgmental bias contributes to the effects. Furthermore, following the approach of Falk et al. (2012), it is conceivable that interindividual differences in the responsiveness to normative influence (e.g., sensitivity for social rejection) could lead to differential effects on individual decision criteria. Hence, a promising avenue for future studies is to combine motivational oriented approaches on social influence with a diffusion model approach. Specifically, future research could experimentally manipulate these two motivational orientations and investigate their effects on the parameters of the diffusion model.

More generally, we think that our research contributes to the field of social cognition and, in particular, to models of impression formation and person construal (e.g., Fiske & Neuberg, 1990; Freeman & Ambady, 2011; Kunda & Thagard, 1996). Here, we want to discuss the models of Kunda and Thagard (1996), and Freeman and Ambady (2011). Both models focus on the idea that social cognition is dynamically driven by bottom-up sensory information and high-level top-down factors (e.g., expectations, motivation). More specifically, these models seek to explain the dynamics of how top-down factors influence lower-levels of person perception. Moreover, both models assume that parallel-constraint-satisfaction principles guide social cognition. Kunda and Thagard’s model presumes that stereotypic and individuated information are given more or less equal priority in perception, and that both types of information are simultaneously integrated into a coherent impression by a constraint satisfaction process. Freeman and Ambady’s dynamic interactive model of person construal more closely examines the initial social categorization process itself. Thus, this model seeks to explore how particular social categories become activated in the first place.

Our diffusion model framework shares a kinship with these models since it also assumes that social perception is driven by bottom-up sensory information and high-level top-down factors. Yet, the diffusion model framework more narrowly applies to relatively fast two-alternative decisions, and assumes that decisions are made by mechanisms that accumulate noisy information until one of two response criteria is reached. Investigating the impact of top-down factors (e.g., social influence) on decision making, one advantage of the diffusion model approach is the identification of different types of bias (i.e., perceptual vs. judgmental bias). Further research should explore the possibility to combine sequential sampling models of decision making (such as the diffusion model) and parallel-constraint-satisfaction models of social cognition.

Limitations

Three limitations of our study need to be put forth. First, as discussed hereinafter, if participants had the wish to see that the majority was correct, it is possible that displaying the majority responses always prior to the visual stimulus had especially promoted the resulting perceptual bias. Thus, on one hand, we cannot generalize our results to situations in which the sensory information is processed before or while social influence is induced (e.g., the Asch-type situation). On the other hand, it is important to note that our experimental set-up (i.e., the majority responses were displayed prior to the stimulus) is not artificial. To illustrate, imagine purchasing a new TV or a new book in an online store. It is very likely that you will first take a look at the customer ratings before delving into all the details of the product. Further research should explore whether and how a perceptual bias operates under conditions where the information is processed while social influence is induced.

Second, the suspicion checks showed that in both experiments, many participants guessed that the study was not only about color perception, but might also examine how their decisions would be influenced by the responses of others. One would expect that this suspicion would at least decrease the influence of the majority response. However, Experiment 1 did not indicate any effect of this suspicion on any of our dependent variables (including diffusion model parameters). Since these participants did not question the authenticity of the majority response, when the majority response was relevant, it represented a comparable source of social information or pressure as for participants without this suspicion. Nevertheless, it would be interesting to experimentally investigate the effects of being aware that one is influenced by others on the cognitive mechanisms mediating social influence.

Third, participants exhibited slight biases in the perception of the color ratios for our stimuli. Overall, participants gave more blue responses than orange responses. This is especially true for relative response rates to stimuli with a 50% orange proportion in the control group. In addition, there were slightly larger effects for orange than for blue majority responses in the experimental condition relative to the control group (see Figures 3 and 5). However, since we found expected effects of the majority response across all levels of orange proportion in the stimulus, this general blue bias did not affect the interpretation of our results about the cognitive mechanism underlying social influence. In future studies, other stimulus material could be used to generalize our results to other types of perceptual decisions (e.g., motion or depth perception).

Conclusion

In conclusion, the core insight that can be derived from our research is that even low-level processing of perceptual
features can be open to social influence. Our results thus extend previous research providing evidence for motivational top-down influences on perceptual processes (e.g., Balcetis & Dunning, 2010; Voss et al., 2008). Moreover, our approach allows the connection of goal-related explanations (Cialdini & Goldstein, 2004; Falk et al., 2012) to the cognitive mechanisms underlying social influence.

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Notes

1. For clarity, we report only the effects which are directly connected to our hypothesis in the Results. The other effects are as follows: The ANOVA also revealed a main effect of the orange proportion showing that the relative frequency of orange responses increased as a function of the orange proportion, $F(4, 192) = 351.26, p < .001, \eta^2_p = .88$. There was a significant two-way interaction of majority response and orange proportion, $F(4, 192) = 10.38, p < .001, \eta^2_p = .18$. In addition, there was a significant two-way interaction between majority relevance and orange proportion, $F(4, 192) = 3.96, p < .004, \eta^2_p = .08$. All other effects were not significant, all $Fs < 1.33$ and all $ps > .259$.

2. The ANOVA also revealed a main effect for the orange proportion, $F(4, 192) = 200.99, p < .001, \eta^2_p = .81$. The two-way interaction of orange proportion and majority relevance also reached significance, $F(1, 48) = 12.84, p < .001, \eta^2_p = .08$. All other effects were not significant, all $Fs < 1.69$, all $ps > .154$.

3. The ANOVA also revealed a main effect for the orange proportion, $F(3, 52) = 413.67, p < .001, \eta^2_p = .94$. There was a significant two-way interaction of majority response and orange proportion, $F(2, 52) = 30.00, p < .001, \eta^2_p = .54$. In addition, there was a significant two-way interaction between majority relevance and orange proportion, $F(2, 52) = 11.40, p < .001, \eta^2_p = .31$.

4. The ANOVA also revealed a significant main effect for the orange proportion, $F(2, 52) = 424.95, p < .001, \eta^2_p = .94$. Furthermore, the two-way interaction of orange proportion and majority response, $F(2, 46) = 3.96, p = .025, \eta^2_p = .13$.

References


