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Unmet expectations about material properties delay perceptual decisions

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ABSTRACT

Based on our expectations about material properties, we can implicitly predict an object's future states, e.g., a wine glass falling down will break when it hits the ground. How these expectations affect relatively low-level perceptual decisions, however, has not been systematically studied previously. To seek an answer to this question, we conducted a behavioral experiment using animations of various familiar objects (e.g., key, wine glass, etc.) freely falling and hitting the ground. During a training session, participants first built expectations about the dynamic properties of those objects. Half of the participants (N = 28) built expectations consistent with their daily lives (e.g., a key bounces rigidly), whereas the other half learned an atypical behavior (e.g., a key wobbles). This was followed by experimental sessions, in which expectations were unmet in 20% of the trials. In both training and experimental sessions, the participant's task was to report whether the objects broke or not upon hitting the ground. Critically, a specific object always remained intact or broke - only the manner in which it did so differed. For example, a key could wobble or remain rigid but never break. We found that participants' reaction times were longer when expectations were unmet, not only for typical material behavior but also when those expectations were atypical and learned during the training session. Furthermore, we found an interplay between long-term and newly learned expectations. Overall, our results show that expectations about material properties can impact relatively low-level perceptual decision-making processes.

1. Introduction

Objects are made of or consist of materials that determine their physical properties. Through a lifetime of experiences, we form long-term expectations about the associations between objects and their physical properties (Buckingham, Cant, & Goodale, 2009; Fleming, Wiebel, & Gegenfurtner, 2013). Based on these learned associations, we can predict future states of objects under different forces (Alley, Schmid, & Doerschner, 2020). For instance, when we hold a teacup in our hand, we will be careful not to drop it because we can predict what will happen if it falls to the ground. On the other hand, we would not worry a lot if a piece of cloth slipped from the grip of our hand. Such expectations are believed to influence behavior through top-down processes and may often be implicit (Kersten, Mamassian, & Yuille, 2004; Kveraga, Avniel, & Bar, 2007; Alley et al., 2020). Indeed we become aware of our expectations only when we encounter a situation in which they are unmet or violated, as illustrated in Fig. 1. Such surprise effects are an important aspect of human experience, and are not only of great interest to researchers but also to artists and designers who use them strategically in their works (see, for example, Ludden, Schifferstein, & Hekkert, 2008; Ludden, Schifferstein, & Hekkert, 2009).

Here we study the effect of long-term and newly acquired, context-dependent expectations about material properties on the speed of relatively low-level perceptual decisions. A great number of studies have shown that observers perceive expected stimuli faster (Stein & Peelen, 2015; Wyart, Nobre, & Summerfield, 2012; Summerfield & de Lange, 2014). Those studies, however, usually focused on the identification of static stimuli. Only a few studies tested the effect of expectation about material properties in dynamic scenes (Alley et al., 2020). In their study, Alley et al. presented participants with computer animations of objects that were falling down and behaving in a predicted or surprising way upon hitting the ground. For example, a teacup could shatter as predicted or, surprisingly, wrinkle like a piece of cloth. The task of the observers was to judge as quickly and as accurately as possible one of four material attributes of the objects in each trial, which were hardness, gelatinousness, heaviness, and liquidity. Alley et al. found that long-

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term expectations bias the perception of material attributes of familiar but not unfamiliar objects. For example, a spoon that wrinkles upon impact was judged harder than a piece of cloth that also wrinkles. Further, they showed that the reaction times were longer in the surprising trials than in expected trials for familiar, but not for unfamiliar objects. In the current study, we use a paradigm similar to that in Alley et al. We present observers with computer animations of familiar objects falling down and behaving in a predicted or surprising way upon hitting the ground. Unlike in the experiment by Alley et al., we do not ask observers to judge material qualities which engage mid to high-level visual processes (Fleming, 2014; Anderson, 2011; Schmid & Doerschner, 2018), but instead target relatively low-level perceptual decisions: the task of the observers was simply to answer the question "did the object break?" Breaking, after hitting the ground, is usually characterized by a typical motion pattern where a uniform vertical trajectory is followed by a fast radial motion pattern. Thus breaking entails a fairly low-level motion cue, i.e., sudden changes in motion direction and speed that can be detected by low-level visual mechanisms (Burr & Ross, 1986). Importantly, in our experiments, breaking objects always break, and non-breaking objects always remain intact upon hitting the ground in both predicted and surprising conditions. Thus, the correct response for the same object, whether surprising or predicted, does not change, eliminating a response preparation confound. With this paradigm and by assessing reaction times (RTs) of observers' judgments about whether breaking occurred, we are able to assess the effect of expectations about material properties on relatively low-level perceptual decisions.

In short, our research question is whether expectations about material properties affect low-level perceptual decisions. We hypothesize that if they do, then RTs should be different under the predicted and surprising conditions. To anticipate, under two different experimental manipulations and with two groups of participants, we found that RTs are indeed longer for the surprising trials. Further, we found an interesting interplay between long-term expectations and newly formed expectations based on context-dependent regularities, for which we propose possible explanations.

2. Materials and methods

2.1. Participants

Twenty-eight participants participated in the experiment. All had normal or corrected to normal vision and were naive to the purposes of the experiment. Participants gave their written informed consent before the first experimental session, in line with the guidelines of the Declaration of Helsinki. Experimental protocols and procedures were approved by the Research Ethics Committee of Bilkent University, Turkey.

2.2. Stimuli presentation

An LCD color reference monitor (Eizo CG2730, 27 inches, 2560 x 1440 resolution, 60 Hz refresh rate) was used for stimulus presentation. The monitor was the only light source in an otherwise completely dark room where the experiment took place. Participants sat on a chair and viewed the monitor from a distance of 60 cm. A chin rest was used to minimize the head movements. The experimental paradigm was programmed with Psychtoolbox (Brainard, 1997) on MATLAB version 2018a (MathWorks Inc., New York, NY, USA).

Stimuli were generated by a professional graphic artist (Aleksa Radakovic) using commercial software (Cinema 4d) and consisted of computer animations of six objects that act in a certain way when dropped on the ground; three of them break upon hitting the ground (breaking objects: wine glass, pot, and teacup) and the other three do not break (non-breaking objects: spoon, key, and rod). Each animation consisted of 46 frames. In all animations, the objects hit the ground in frame number 15. There were two animations for each object. In one set of animations, objects behaved in a natural way upon hitting the ground. Specifically, breaking objects shattered, and non-breaking objects bounced rigidly after they hit the ground. In the other set, objects behaved in an atypical way upon hitting the ground: breaking objects graveled and non-breaking objects wobbled. Fig. 2 shows examples of these natural and atypical behaviors.

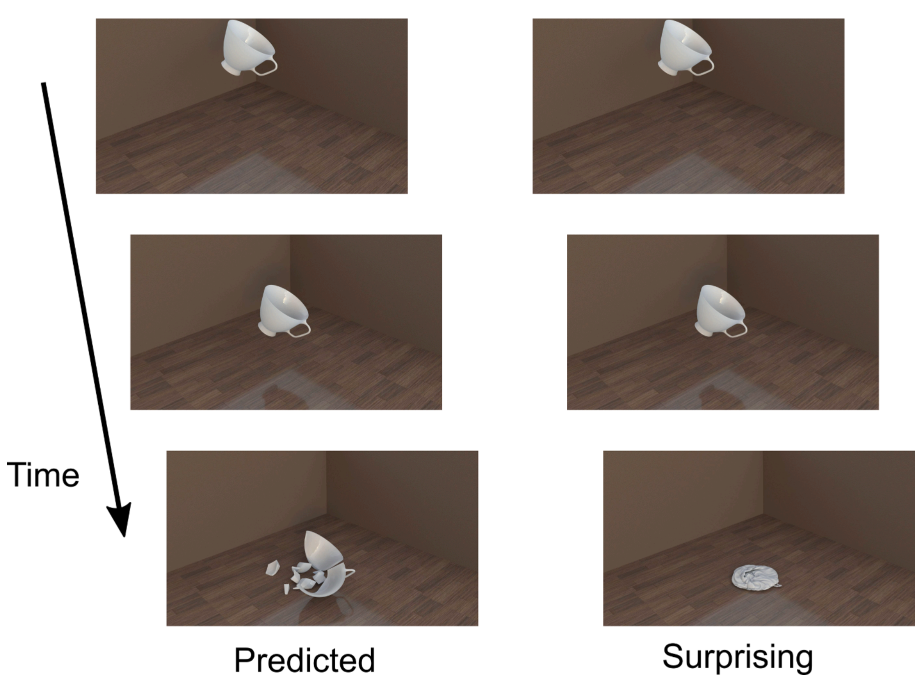

Fig. 1. As soon as we see a teacup start falling down, our visual system predicts what might happen to it: if not caught, the cup will hit the ground and shatter. If the cup wrinkles as a piece of cloth upon hitting the ground, we will be surprised and even amazed. Because our expectations and the visual input mismatch (Alley et al., 2020).

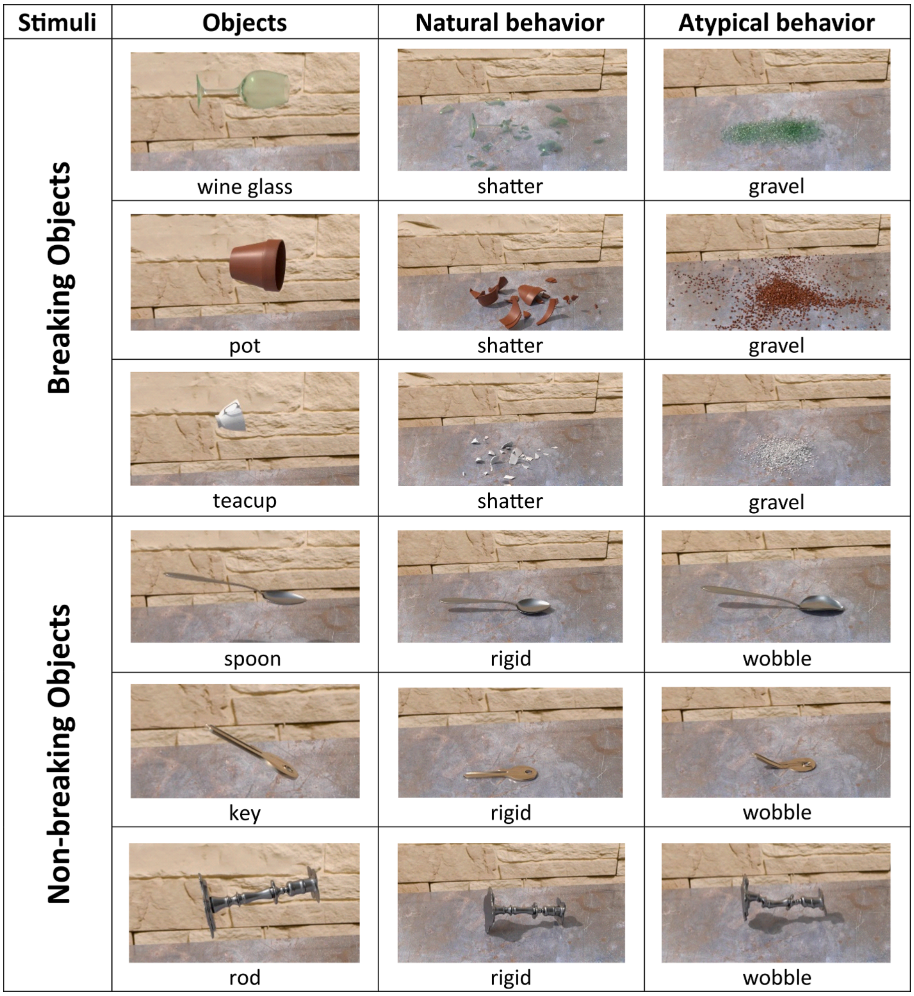

Fig. 2. Six objects used as stimuli and their natural and atypical behaviors. For the participants in the 'natural group,' natural behavior was predicted, and atypical behavior was surprising. For the participants in the 'atypical group,' atypical behavior was predicted, and natural behavior was surprising. These expectations were formed through a training session before the main experiment. See text and Fig. 3 for details about the training procedure. Click here to view or download a video clip showing sample stimuli. [Please refer to video "sampleStimuli.mp4" under the supplementary section].

2.3. Experimental design

Participants were divided into two groups; natural group and atypical group. Each participant underwent a training session followed by an experimental session. During the training session, participants in the natural group were presented with animations where objects behaved naturally, whereas participants in the atypical group were presented with animations where objects behaved atypically (20 trials for each object). Thus, the newly formed context-dependent expectations about an object's material properties in the atypical group were different from the already existing long-term expectations.

During the experimental session, 10 animations were shown for each object. Of those 10, 8 were the same as in the training session (naturally behaving objects for the natural group, atypically behaving objects for the atypical group). We call these predicted trials. The remaining 2 trials were from the untrained category (atypically behaving objects for the natural group, naturally behaving objects for the atypical group). We call these surprising trials. The order of presentation was randomized in all sessions. Fig. 3 shows example sequences of trials for training and testing sessions for both groups (natural & atypical).

All sessions started with an instruction screen, followed by the animations as soon as any key was pressed. All animations were preceded by a 1-s blank screen with a central fixation cross. Each animation was 1.53 s long (46 frames, 30 frames per second). The task was to answer the question, "Did the object break?" by pressing the corresponding keys for "yes" and "no" on the keyboard after the object hit the ground. In the training session, an error sound was delivered if the participant answered the question before the object hit the ground. Reaction times were measured from the time an object made an impact on the ground (15th frame) to the time when the participant pressed a key. The next trial did not start until the observer responded.

2.4. Analysis

Analyses were performed on MATLAB version 2018a (MathWorks Inc., New York, NY, USA) and RStudio (RStudio Team, 2020). For the training session, data from trials in which reaction times were negative (i.e., a response was made before the object hit the ground) were excluded from analyses. For the experimental session, data from trials in which reaction times were negative or did not fall within the $\pm$ 3SD of the mean were excluded from analyses (a total of 24 out of 1680 data points excluded).

The histogram of the raw reaction time data indicated that they were skewed and not normally distributed. To remedy this, before any subsequent analysis, we transformed the RTs using a Box-Cox transformation. Note, to make interpretation of the results easier, we use raw RTs in the figures and when we report means in the text. Next, we ran two omnibus Linear Mixed Models (LMMs), one for the training RTs, and one for the experimental RTs, using the 'lme4' package (Bates, Mächler, Bolker, & Walker, 2015) in RStudio (RStudio Team, 2020). For both models, the transformed reaction times were included as the dependent variable, and the between-subject variance was estimated using a random intercept in the model. For the training, we wanted to investigate to what extent the training modulated reaction times in natural and atypical groups. To answer this question, we wanted to contrast RTs in the beginning (first five trials) and the end of the training session (last

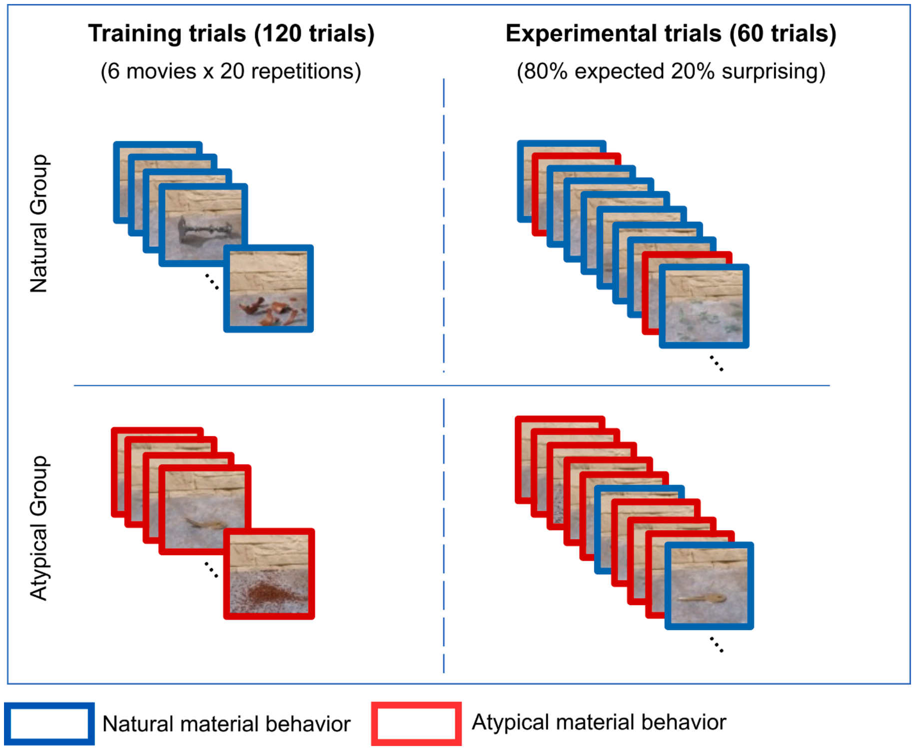

Fig. 3. Experimental Design: Each participant underwent a training session before the experimental session. Participants in the natural group were trained on naturally behaving objects, while participants in the atypical group were trained on atypically behaving objects. In the experimental session, contextual expectations formed in training sessions were unmet in 20% of the trials.

five trials) for each group (we call this predictor 'time'). Thus our 'training' LMM model included time, group, and their interaction as fixed effects:

$$RT \sim Time \times Group + (1|participant\ ID). \tag{1}$$

For the experiment, we wanted to find out to what extent RTs might be modulated by the experimental condition (predicted vs. surprising), the type of the object, i.e., how its material reacted to impact force (breaking vs. non-breaking), and the group (natural vs. atypical). Thus the 'experiment' model included condition, group, object, and their two-way and three-way interactions as fixed effects:

$$RT \sim Condition \times Group \times Object + (1|participant\ ID). \tag{2}$$

To calculate the significance of the fixed effects, we used the 'lmerTest' package (Kuznetsova, Brockhoff, & Christensen, 2017), which uses Satterthwaite's method to estimate the degrees of freedom and generate p-values for linear mixed models. Any potential post hoc analysis for pairwise comparisons of estimated marginal means was done with the 'emmeans' package (Lenth, 2023) using a Tukey correction. Percent correct responses were compared between expected and surprising conditions for each group using a two-tailed Student's *t*-test, correcting for multiple tests (alpha = 0.025/2).

3. Results

3.1. Training session

Using linear mixed model analysis that included time (first vs. last five time points) and group (natural vs. atypical) and their interaction as fixed effects, we found that time ($F(1) = 63.3, p < 0.001$), and the interaction of time and group ($F(1) = 19.06, p < 0.001$) significantly modulated RT. The main effect of group was not significant. To follow up the interaction, we conducted pairwise comparisons of RTs within each group and found that only for the atypical group, the difference in RT between initial and final trials was significant ($p < 0.001$). Fig. 4 shows the mean RTs as a function of trial number in the training session as well as the mean RTs for only the first and last five trials of the training for each group. The latter clearly illustrates the significant interaction found in the LMM, which suggests that training effects were strongest for the atypical group.

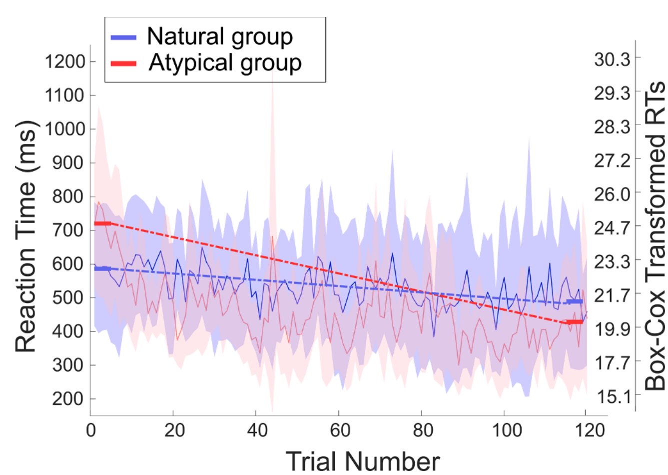

Fig. 4. Reaction times (RTs) from the training sessions of both groups as a function of trial number. The blue solid line shows mean RTs for the natural group (across 14 participants), and the pink line shows mean RTs for the atypical group (across 14 participants). Shaded regions are the 95 percent confidence interval around the mean. Thick horizontal solid lines show mean RTs on the first and last 5 trials. Overall, RTs get shorter as the session progresses. This training effect is stronger for the participants in the atypical group, who were trained on the atypical behavior.

3.2. Experimental session

Before conducting the LMM analysis on RTs, we wanted to verify that there was no difference between expected and surprising conditions in terms of performance (percent correct) in the behavioral task (indicating whether an object broke or not). A two-tailed Student's t-test yielded no statistically significant differences between the percentage of correct responses of predicted (average 98.6%) and surprising (average 98.5%) conditions. Next, using linear mixed model analysis that included condition (predicted vs. surprising), group (natural vs. atypical), object (breaking vs. not breaking), and their interaction as fixed effects, we found that condition ($(F(1) = 60.44, p < .001)$, object ($F(1) = 16.54$, $p < .001$), the interactions between object and group ($F(1) = 29.95$, $p < .001$), and object and condition ($F(1) = 15.66, p < .001$), as well as the interaction between condition, group, and object ($F(1) = 17.81$, $p < .001$), all significantly modulated RT. Table 1 reports the corresponding estimates of all fixed effects.

Figs. 5–7 aid in interpreting the significant effects found in the LMM analysis. Overall, across conditions, RTs were longer in the surprise condition (meanRT = 619.2 ms) than in the predicted one (meanRT = 510 ms; Fig. 5, difference between dark and light blue bars). The same pattern is present in nearly every participant (Fig. 6) and and is also manifested in the negative value of the estimate of the predictor condition (Table 1): the condition 'predicted' is a negative predictor of RT surprising (which is used as the reference category in the model).

The presence of this significant main effect, in essence, would answer our main research question, namely whether expectations affect the speed of making perceptual decisions and whether participants take longer when their expectations are unmet. The main effect of condition, however, has to be interpreted in light of the two- and three-way interaction(s) with object and group, which we will focus on next.

The interaction between condition and group can be understood by inspecting Fig. 5: while the difference between predicted and surprise conditions was significant for both groups ($p < 0.01$), it was somewhat larger in the natural than in the atypical group. We also found an interaction between condition and object, with RTs under the surprising condition for the non-breaking objects (mean = 671 ms) being, on average, significantly longer than those for the breaking objects (mean = 576.5 ms, $p < .001$), whereas RTs under the predicted condition did not differ for the two object types (mean for breaking = 510.1 ms, mean for non-breaking = 509.9 ms, $p = 0.99$). Further, Fig. 7 reveals the cause for the significant three-way interaction between condition, group, and object: the difference between the RTs of predicted and surprising conditions was significant only for the non-breaking objects in the natural group ($p < 0.001$), and conversely, only for the breaking objects in the atypical group ($p < 0.05$). All significant pairwise comparisons are listed in Table 2.

Table 1
Linear mixed model fixed effect estimates from the experimental session. Estimates and standard errors correspond to Box-Cox transformed RTs. (Significant effects are in bold.)

Predictors	Estimates	CI	p-Value
Intercept	26.04	24.47 – 27.60	**< 0.001**
Condition (Predicted)	−0.91	−1.13 – −0.68	**< 0.001**
Object (Breaking)	−0.47	−0.70 – −0.25	**< 0.001**
Group (Natural)	0.76	−0.81 – 2.33	0.342
Condition (Predicted) x Object (Breaking)	0.46	0.23 – 0.69	**< 0.001**
Condition (Predicted) x Group (Natural)	−0.22	−0.45 – 0.00	0.054
Object (Breaking) x Group (Natural)	−0.64	−0.87 – −0.41	**< 0.001**
Condition (Predicted) x Object (Breaking) x Group (Natural)	0.49	0.26 – 0.72	**< 0.001**

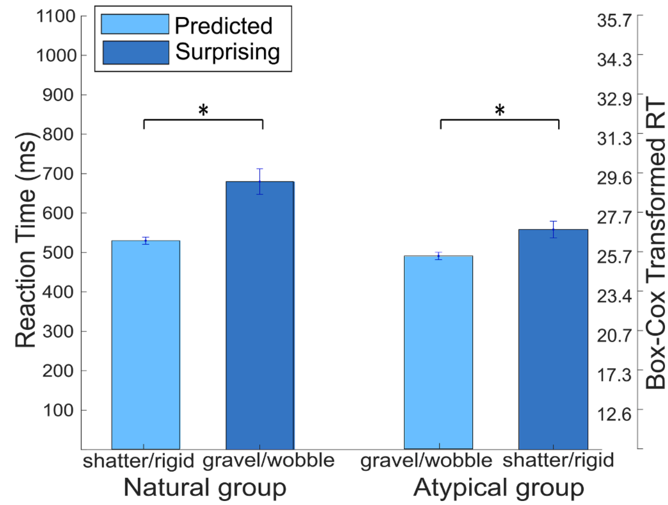

Fig. 5. Mean RTs of predicted and surprising conditions averaged across participants. When expectations are unmet, whether natural or atypical, perceptual decisions are delayed (post hoc pairwise comparison of estimated marginal means are significant, *: $p < 0.01$). This effect tends to be stronger in the natural group. The error bars represent SEM.

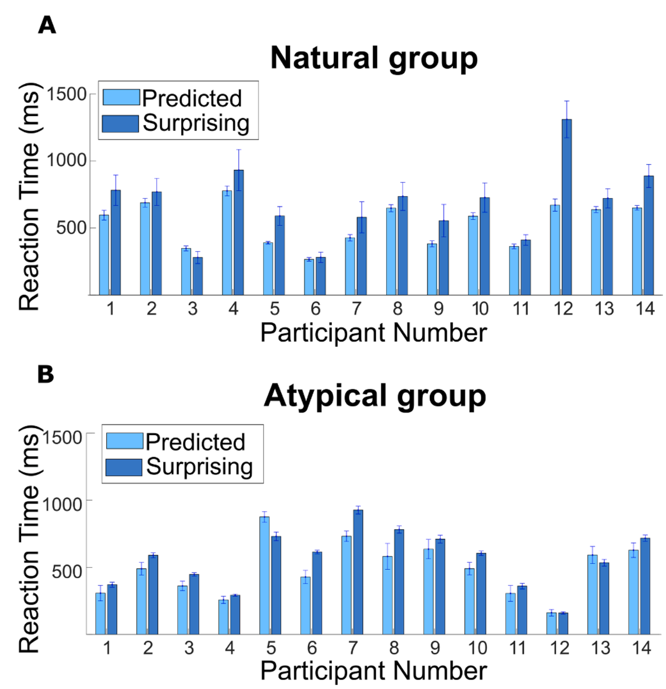

Fig. 6. Mean RTs per participant in the experimental session for (A) natural and (B) atypical groups. Light and dark blue bars denote mean RTs in the predicted and surprising conditions, respectively. Error bars correspond to SEM.

Taken together, these interactions do not invalidate the main effect of condition; instead, they paint a more interesting picture of how expectations affect the speed of making perceptual decisions, which we will discuss below.

4. Discussion

Here we studied the effect of expectations about material properties on the speed of relatively low-level perceptual decisions. We presented computer animations of objects falling down and asked the participants to report as soon as possible whether the objects broke or not upon hitting the ground. We found that participants were slower to make this

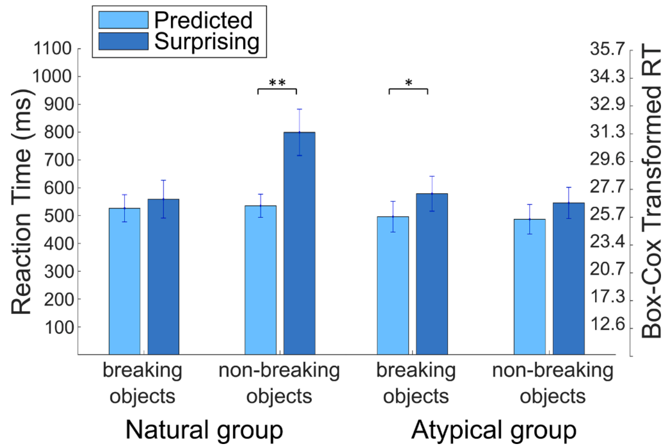

Fig. 7. Mean RTs in the experimental session for breaking and non-breaking objects. The left side shows the results of the natural group, while the right side shows the results of the atypical group. Posthoc pairwise comparison of estimated marginal means is marked significant with ** for $p < 0.001$ and * for $p < 0.05$. Error bars represent SEM. For all significant pairwise comparisons, see Table 2.

Table 2
Follow-up contrasts for the three-way interaction of condition, group, and object that we found in the experiment. Only significant comparisons are listed. PRE: predicted, SUR: surprising, NAT: natural group, ATP: atypical group, BRK: breaking object, NBR: non-breaking object.

contrast	estimate	SE	df	t.ratio	p.value
PRE BRK NAT - SUR NBR NAT	−4.4832	0.4632	1622.00	−9.679	**<.0001**
SUR BRK NAT - SUR NBR NAT	−4.1282	0.5887	1622.02	−7.013	**<.0001**
PRE NBR NAT - SUR NBR NAT	−4.1656	0.4630	1622.00	−8.996	**<.0001**
SUR NBR NAT - PRE NBR ATP	5.5278	1.6474	29.82	3.355	**0.0397**
PRE BRK ATP - SUR BRK ATP	−1.4240	0.4651	1622.00	−3.061	**0.0463**
SUR BRK ATP - PRE NBR ATP	1.6902	0.4657	1622.01	3.629	**0.0071**

judgment when their expectations about the material properties were not met. Furthermore, this was true even when participants were trained to predict an atypical behavior, for example, that a candle stick wobbled as if made of jelly. The pattern of our results can not be explained by motor response preparations because whether under the predicted or surprising condition, for a given object, the correct response was always the same: breaking objects always broke, and intact objects always remained intact. Motion statistics, on the other hand, might have affected the RTs. For example, it could be easier to decide that an object remains intact with the motion statistics of a rigid body compared to a gelatinous one. Those low-level motion statistics alone, however, cannot completely explain the differences between the two experimental groups. Because if motion statistics alone determined the responses, we would find the same pattern of RTs for both groups; namely, participants would always be quicker on the trials of a certain motion type, for example, on the trials of rigid body motion.

Expectations about material properties affect low-level perceptual processes. Our main finding is in line with previous studies. For example, Alley et al. (2020) found that unmet expectations delay participants' decisions about material attributes. But unlike in most previous literature, in our study, the participant's task was not about material attributes. And the participants did not need to attend to and process the material properties; they only needed to analyze the motion patterns after the objects hit the ground. Thus, a sensible strategy could have been to ignore or down-weigh the object-material associations and instead focus entirely on the low-level motion patterns after the impact. Yet, we find that participants' decisions were nevertheless affected by their expectations about material properties. This demonstrates that high-level expectations can affect low-level perceptual processes, even when those expectations are task-irrelevant.

Training alters expectations. Our daily subjective experiences and previous research on the topic (Alley et al., 2020; Paulun, Schmidt, Assen, & Fleming, 2017; Schmid & Doerschner, 2018; Schmidt, Paulun, Assen, & Fleming, 2017) suggest that we form associations between an object and its typical material properties. These associations not only help us to recognize and identify the object and materials efficiently but also help in action planning and guiding our interaction with them (Buckingham et al., 2009; Doerschner et al., 2011; Sutter, Drewing, & Müsseler, 2014).

Some long-term expectations are "stubborn" and do not easily change, but some can be altered under experimental conditions (Yon, de Lange, & Press, 2019; de Lange, Heilbron, & Kok, 2018). For example, Adams, Graf, and Ernst (2004) showed that "light from above" prior could be altered when participants are trained with haptic feedback. Similarly, Sotiropoulos, Seitz, and Seriès (2011) showed that "slow speed prior", which explains many motion and direction illusions, can be altered through training sessions. The pattern of RTs we found in the current study is consistent with this literature. We found that RTs of the atypical group were longer under the surprising condition compared to the predicted condition, even though the predicted atypical behaviors were in conflict with the long-term expectations. In essence, participants learned new context-dependent expectations during the training session.

RT data from the training session provides further insights into the progress of this learning. Firstly, the decrease in RTs was larger for the atypical group compared to the natural group. This was anticipated because only in the atypical group did participants learn new associations and form new context-dependent expectations. At the beginning of the training sessions, RTs of the atypical group were longer than those of the natural group, which was also anticipated because the object behaviors were atypical and not predicted based on long-term expectations. But as the session progressed, the atypical group participants started to learn to expect the atypical behaviors in the context of the experiment, and their RTs decreased. Towards the end of the session RTs of the atypical group were equal to, and even slightly lower than RTs of the natural group. This further reduction might be related to an 'oops' factor, whereby a sequence of asynchronously presented mismatching cues can lead to efficient learning (Adams, Kerrigan, & Graf, 2010).

Interplay between long-term expectations and context-dependent regularities. The overall effect of expectations, i.e., a larger RT difference between predicted and surprising conditions, tended to be stronger in the natural group compared to the atypical group. For the natural group, where long-term expectations and context-dependent learned regularities were consistent, a strong expectation effect was indeed anticipated. Whereas for the atypical group, long-term expectations, which can often be strong (Seriès & Seitz, 2013), were in conflict with the newly acquired expectations. This conflict could have reduced the overall strength of the newly acquired context-dependent expectations in the atypical group. Further scrutiny revealed a significant effect of expectation for intact objects but not for breaking objects in the natural group. Conversely, for the atypical group, there was a significant effect for breaking objects but not intact objects. This finding might seem puzzling at first, but it can be explained by different strengths of long-term expectations. Long-term expectations for the non-breaking objects used in the experiment, such as the candlestick being rigid - rather than gelatinous, might be very strong, leading to the significant effect found for those objects in the natural group. These long-term expectations, however, strongly conflict with the context-dependent regularities for the atypical group and thus produce weaker new expectations and result in no effect for the non-breaking objects in that group. Conversely, for the breaking objects used in the experiment, long-term expectations to shatter might not be much stronger than the long-term expectations to gravel, leading to little or no effect of expectation in the natural group. But this time, because the long-term expectations are weak, the newly-acquired expectations are stronger, and this results in a significant effect for the atypical group. Essentially, the pattern of our results indirectly reveals novel facts about the strength of various expectations about material dynamic properties. Note that, in principle, these conceptual arguments can be formalized in a Bayesian updating model, in which posteriors are computed iteratively in time (Urgen & Boyaci, 2021b; Bitzer, Park, Blankenburg, & Kiebel, 2014). Likewise, more mechanistic, iterative predictive processing models could be employed to establish a link between behavior and neuronal activity (Urgen & Boyaci, 2021a; Heeger, 2017).

5. Conclusion

To conclude, we found that unmet expectations about dynamic material properties delay perceptual decisions. We argue that high-level expectations about material properties affect relatively low-level perceptual processes even when those expectations are not directly task-relevant. Furthermore, we show that through training, participants form new context-dependent expectations. Those newly formed context-dependent expectations and long-term expectations together shape the perceptual processes.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgment

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Appendix A. Supplementary material

Supplementary data associated with this article can be found, in the online version, at https://doi.org/10.1016/j.visres.2023.108223.

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