EEG decoding reveals neural predictions for naturalistic material behaviors

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Abstract

Material properties like softness or stickiness determine how an object can be used. Based on our real-life experience, we form strong expectations how objects should behave under force, given their typical material properties. Such expectations have been shown to modulate perceptual processes, but we currently do not know how expectation influences the temporal dynamics of the cortical visual analysis for objects and their materials. Here, we tracked the neural representations of expected and unexpected material behaviors using time-resolved EEG decoding in an expectation-of-violation paradigm, where objects fell to the ground and deformed in expected or unexpected ways. Our study yielded three key results: First, both objects and materials were represented rapidly and in a temporally sustained fashion. Second, expected material behaviors were represented more strongly than unexpected behaviors within 190ms after the impact, which might indicate additional processing demands when expectations are unmet. Third, general signals of expectation fulfillment that generalize across specific objects and materials were found within the first 150ms after the impact. Together, our results provide new insights into the temporal neural processing cascade that underlies the analysis of real-world material behaviors. They reveal a sequence of predictions, with cortical signals progressing from a general signature of expectation fulfillment towards increased processing of unexpected material behaviors.

Introduction

Many objects in our environment are made of a particular material, like porcelain, fabric, or rubber. Material properties critically determine how an object is used or interacted with. Thus, the ability to visually recognize material qualities quickly and correctly is important for planning actions and interactions (Buckingham et al., 2011, Klein et al. 2020).

Humans are able to make judgments about optical and non-optical material qualities, based on *visual* information alone (Adelson, 2001; Fleming, 2017; Kentridge & Chadwick, 2014; Paulun et al., 2019; Schmidt et al., 2017; Schmid & Doerschner 2018; Schmid et al. 2021; van Assen et al. 2020). One possible explanation of this remarkable ability to infer non-optical material qualities, like softness or stickiness, from images is that we have learned over a lifetime to associate hand actions and haptic sensations with visual consequences of interactions (e.g., characteristic deformations).

This type of associative learning leads to strong expectations about how a material will behave under external forces (Alley et al., 2020; Bates et al., 2015; Paulun et al., 2017). For example, Bates et al. (2015) showed that humans can efficiently predict how liquids of different viscosities flow around solid obstacles. In our own work, we recently showed that existing expectations (i.e., those acquired through life-long learning) about the typical material properties of objects modulate perception (Alley et al., 2020; Malik et al., 2022). In our experiments, participants saw familiar objects (chairs, cups, custard) and unfamiliar novel shapes made of the same material as the familiar ones, fall to the ground. Upon impact the objects either behaved as expected (e.g., a cup shattering or a custard wobbling) or unexpectedly (e.g., a cup turning into liquid or wobbling). Only in the familiar object condition, we found that property ratings of the objects were systematically biased towards participants' expectations about the material behavior and that unmet expectations were associated with longer response times that index additional processing demands. Together, these results demonstrate that the perception of real-world objects is invariably tied to expectations about their material behaviors.

We currently do not know how material behaviors are extracted across the neural visual processing cascade. More specifically, it is unclear at which stages of the processing cascade expectations about material behaviors modulate the cortical analysis of objects and their materials. To resolve these open questions, we devised an EEG experiment, in which we employed a variation of our previous paradigm where participants viewed real-world objects falling to the ground and exhibiting expected or unexpected material behaviors on impact. We then used time-resolved EEG decoding (Grootswagers et al., 2017) to track the representation of expected and unexpected material behaviors.

Materials and Methods

Participants

Twenty-five healthy adults (17 female, 8 male; mean age: 28.7 years, SD=7.4) participated in the experiment. All participants had normal or corrected-to-normal vision. Participants provided written informed consent before the experiment and received a monetary reimbursement. The study protocol was approved by the general ethical committee of Justus-Liebig-University Gießen. All experimental protocols were in accordance with the Declaration of Helsinki.

Stimuli

Stimuli were eight full-color video renders (2s duration, 24Hz frame rate) depicting objects (chair, milk, custard, glass) falling from a fixed starting point down to the ground (Fig. 1a). Upon hitting the ground, an object either displayed its expected (e.g., custard wobbling on impact) or an unexpected (e.g., custard shattering to pieces on impact) material behavior (Fig. 1b). To create expected and unexpected stimuli, material behaviors were swapped among two pairs of objects: (1) the chair could stay rigid or splash like a liquid and the milk could splash or become rigid, and (2) the custard could wobble or shatter to pieces and the glass could shatter to pieces or wobble (Fig. 1b). The videos were used in previous behavioral studies on material perception and are available at https://doi.org/10.5281/zenodo.2542577.
The objects were rendered at approximately the same size so that they would behave in a similar way under gravity and were matched for motion energy across the expected and unexpected material behaviors (see Alley at al., 2020, for a more detailed description of the stimuli).

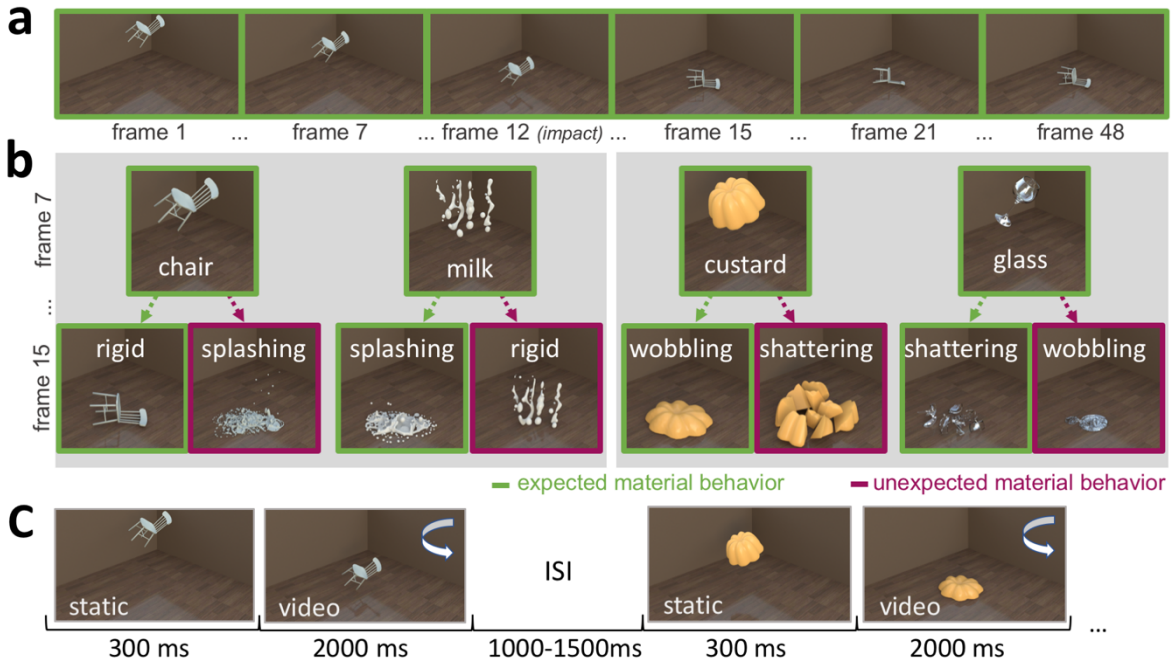

Figure 1. Stimuli and paradigm. *(**a**) Example movie sequence for the object chair, subsampled at different frames throughout the video. (**b**) Illustration of the different object-material behavior combinations in our experiment at two time points during the animation (frames 7 and 15). Green color denotes expected material behaviors, e.g., the chair falling to the ground rigidly, purple color denotes unexpected material behaviors, e.g., the chair splashes upon hitting the ground. To create the unexpected material behaviors, two objects "swapped" material behaviors between them: chair - milk and custard - glass. Stimuli can be downloaded at https://doi.org/10.5281/zenodo.2542577. (**c**) Experimental paradigm. Participants viewed the videos in a random sequence while detecting occasional luminance dims in the whole stimulus.*

Paradigm

Stimulus presentation was controlled using the Psychtoolbox (Brainard, 1997) for Matlab. Stimuli were presented on an AORUS FI32Q monitor at a refresh rate of 170Hz. The whole videos subtended 21 degrees by 16 degrees visual angle. Each trial (Fig. 1c) started with a 300ms static presentation of the first video frame. After that, the remaining video was played (47 frames with a frame time of 41.2ms each), with the object's material behavior becoming apparent upon impact after 712ms relative to the

first onset of the static presentation (i.e., on the 12th video frame). Participants were instructed to maintain central gaze and to refrain from blinking during the stimulus presentation. They were further asked to respond to slight, but noticeable luminance dims in the videos by pressing the space bar. These luminance dims could only occur between the 13th and 36th frame, with onsets drawn from a truncated normal distribution peaking at the 33rd frame (i.e., 1,577ms after onset). We made targets more likely to appear late in the trial to ensure sustained attention during the trial. Participants on average detected the luminance dims in 80% of the cases (due to technical problems, responses were only recorded for 16 participants). Target trials were not used in the EEG analyses. Trials were separated by an inter-trial interval randomly varying between 1,000 and 1,500ms. The whole experiment featured 960 trials (including 96 target trials), and each video was presented equally often. Trial order was fully randomized.

EEG recording and preprocessing

EEG signals were recorded using an Easycap 64-channel system and a Brainproducts amplifier, at a sample rate of 500Hz. Electrodes were arranged according to the standard 10-10 system. Data preprocessing was performed using the FieldTrip toolbox (Oostenveld et al., 2011) for Matlab. The data were epoched from -500ms to 2800ms relative to stimulus onset, band-stop filtered to remove 50Hz line noise, re-referenced to the average across all electrodes, downsampled to 200Hz, and baseline corrected by subtracting the mean pre-stimulus signal. After that, noisy channels were removed by visual inspection. Eye artifacts were removed using independent component analysis (ICA) and visual inspection of the resulting components. Finally, the data were further downsampled to 100Hz.

Decoding analyses

Decoding analysis was performed using the CoSMoMVPA toolbox (Oosterhof et al., 2016) for Matlab, and carried out separately for each participant. All analysis were performed in a time-resolved fashion (Grootswagers et al., 2017), that is, separate analyses were conducted at each time point (i.e., for steps of 10ms). Specifically, linear discriminant analysis (LDA) classifiers were always trained on one subset of the data and tested on a disjoint subset of the data (see below for details). Classifier accuracies were averaged across all possible train-test splits to yield a time course of decoding accuracies. All decoding time courses were smoothed with a 3 time-point (i.e., 30ms) moving average (Kaiser et al., 2016). Statistical testing was then performed across participants (see below for details). We performed multiple decoding analyses to retrieve complementary stimulus attributes, which are detailed in the following.

Object decoding. Each object (chair, milk, custard, glass) produced data from expected and unexpected material behavior trials. Here, our goal was to decode between the different objects shown on each trial, irrespective of their material behavior. This was done by splitting the data into 10 equally sized chunks: we assigned 90% of trials for each unique video to the training set and the remaining 10% of trials to the testing set. Each individual video thus appeared both in the training and testing set. During training, different labels were assigned to videos containing the four objects, and during testing classifiers had to predict the correct object label. The classification procedure was repeated 10 times, until each chunk served as the test set once; accuracies were averaged across these 10 repetitions. Performing the classification in this manner allows for the possibility that the classifier not necessarily picks up on object identity per se, but instead on idiosyncratic aspects of the movies, e.g., the specific material behaviors of each object. Therefore, in order to rule out this possibility we also trained classifiers on half of the available trials and tested them on the other half of trials. These halves were chosen so that classifiers were always trained on a

different material behavior than they were later tested on, thus only allowing them to capitalize on the object identity and not the material behavior. Results were averaged across 16 possible assignments of these halves and across both train-test directions (e.g., train: chair rigid; test: chair liquid and vice versa, for each of the four objects).

Material decoding. Each material behavior (rigid, splashing, wobbling, shattering) produced data from expected and unexpected trials. Here, we decoded between the materials shown on each trial, irrespective of the object exhibiting the behavior. This was done by splitting the data into 10 equally sized chunks: we assigned 90% of trials for each unique video to the training set and the remaining 10% of trials to the testing set. Each individual video thus appeared both in the training and testing set. During training, different labels were assigned to videos containing the four materials, and during testing classifiers had to predict the correct material label. The classification procedure was repeated 10 times, until each chunk served as the test set once; accuracies were averaged across these 10 repetitions. Performing the classification in this manner allows for the possibility that the classifier not necessarily picks up on material behavior per se, but instead on idiosyncratic aspects of the movies, e.g., the specific object properties associated with a specific material behavior. Therefore, in order to rule out this possibility we followed a similar logic as above and trained classifiers on half of the available material trials and tested them on the other half of trials. These halves were chosen so that classifiers were always trained on a different object than they were later tested on, thus only allowing them to capitalize on the material property and not the identity of the object that exhibited the behavior. Results were averaged across 16 possible assignments of these halves and across both train-test directions.

Decoding for expected and unexpected material behaviors. Here, we performed two separate decoding analyses, which separately tracked the representations for expected and unexpected object-material combinations. For each analysis, we only used the data for videos with expected or unexpected material behaviors, respectively. Data were split into 10 equally sized chunks: we assigned 90% of trials for each unique video to the training set and the remaining 10% of trials to the testing set. Each individual video thus appeared both in the training and testing set. During training, different labels were assigned to the four different videos, and during testing classifiers had to predict the correct video. The classification procedure was repeated 10 times, until each chunk served as the test set once; accuracies were averaged across these 10 repetitions. By comparing the decoding timeseries for the expected and unexpected material behaviors, we could infer whether decoding is enhanced for unexpected material behaviors, where unpredictability may require additional visual processing.

Expectation decoding. Here, we directly decoded between trials that displayed an expected or an unexpected material behavior. First, this was done by splitting the data into 10 equally sized chunks: we assigned 90% of trials for each unique video to the training set and the remaining 10% of trials to the testing set. Each individual video thus appeared both in the training and testing set. During training, two different labels were assigned to videos, reflecting whether the material behavior was expected or unexpected, and during testing classifiers had to predict the correct expectation label. The classification procedure was repeated 10 times, until each chunk served as the test set once; accuracies were averaged across these 10 repetitions. Second, to abstract away from specific objects and materials shown on individual trials, we trained classifiers on the first pair of object and material behaviors (chair/milk – rigid/liquid) and tested classifiers on the second pair of objects and material behaviors (custard/glass – wobbling/shattering), or vice versa. As classifiers encountered different objects and material behaviors in the training and test sets, successful decoding in this analysis

reveals a general signal of expectation fulfillment. Results were averaged across both train-test directions.

Statistical testing

Decoding accuracies were tested against chance level using one-sided t-tests, separately across time. For comparing decoding accuracies, two-sided tests were used. P-values were corrected for multiple comparisons across time using false-discovery-rate (FDR) corrections. Only tests after stimulus onset and tests yielding at least two consecutive timepoints reaching statistical significance were considered. T-statistics and Cohen's d as a measure of effect size are reported for all peak effects.

Data availability

Stimuli are available on at *https://doi.org/10.5281/zenodo.2542577*. Data are available at *https://osf.io/2bqav*. Other materials are available on request.

Results

To track the emergence of neural representations of objects and material behaviors, we used time-resolved multivariate decoding analyses. These analyses yielded a time course of when objects and materials are discriminable from EEG sensor patterns, as well as when representations are influenced by expectations about material behaviors.

Object decoding

To track object representations across time, we trained classifiers on discriminating videos that contained different objects, irrespective of the material behavior (Fig. 2a). These classifiers could successfully predict the objects from 90ms and across the whole epoch (peak at 720ms, t[24]=8.3, d=1.7). This emergence of object decoding is consistent with decoding of objects in static images (Contini et al., 2017). As classifiers trained and tested on the same trials can capitalize on idiosyncrasies in individual stimuli, which include the material behavior, we performed a second analysis where classifiers were trained on discriminating the objects for one set of material behaviors and tested on the same objects exhibiting different material behaviors. In this analysis, objects were successfully decoded from 100ms to 950ms (peak at 720ms, t[24]=7.3, d=1.5), showing that object representations did not persist more than 300ms after the object hits the ground.

Material decoding

To track material representations across time, we trained classifiers on discriminating videos that contained different material behaviors, irrespective of the objects that exhibited these behaviors (Fig. 2b). These classifiers could successfully predict the material behaviors from 100ms and across the whole epoch (peak at 970ms, t[24]=10.2, d=2.0). As classifiers are again trained and tested on the same trials and could thus also pick up on object information, we performed a second analysis where classifiers were trained on discriminating the material behaviors for one set of objects and tested on the same material behaviors exhibited by a different set of objects. In this analysis, material behaviors were successfully decoded from 950ms to 2,310ms (peak at 1,130ms, t[24]=5.5, d=1.1), providing evidence for a neural representation of materials that is formed around 240ms after the object hits the ground.

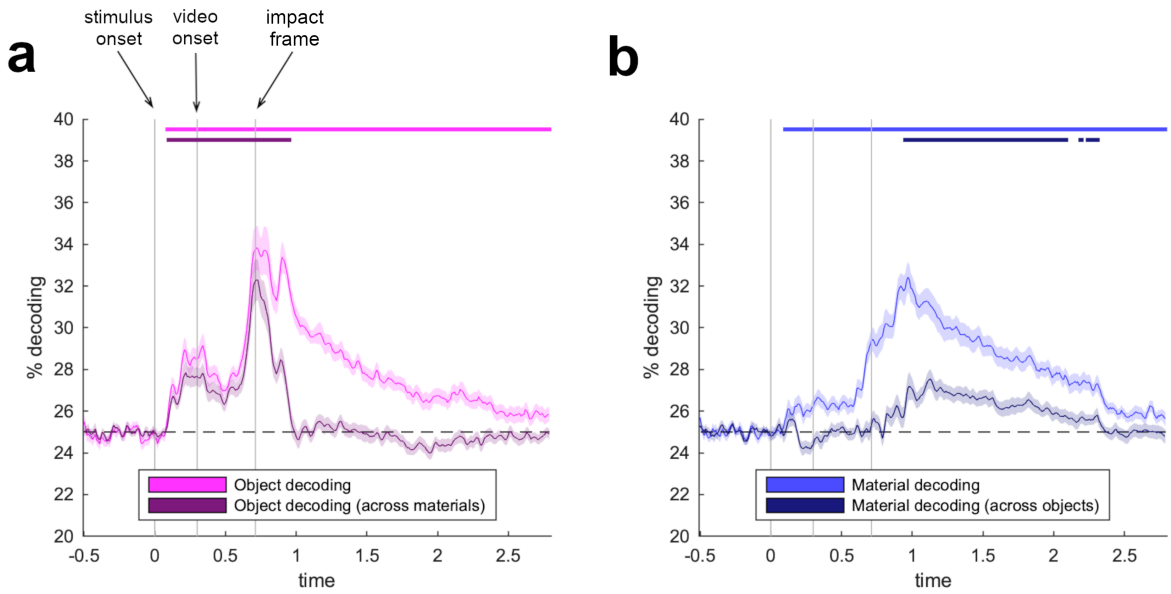

Figure 2. Neural representations of objects and materials across time. *Both objects* ***(a)*** *and materials* ***(b)*** *were reliably decoded from EEG signals. When classifiers needed to generalize across the different material behaviors, object decoding vanishes about 300ms after the object hits the ground (impact frame). When classifiers needed to generalize across the different objects, material decoding emerged 240ms after the impact frame, which is when the material behavior is revealed. Error margins represent standard errors of the mean. Significance markers denote p<0.05 (corrected for multiple comparisons across time).*

Decoding for expected and unexpected behaviors

We next asked whether expected and unexpected material behaviors give rise to cortical representations of different qualities: that is, are unexpected material behaviors better discriminable, because unmet predictions lead to recurrent (Urgen & Boyaci, 2021) or enhanced processing of the visual input? To answer this question, we trained two separate classifiers on discriminating videos that contained an expected material behavior and on discriminating videos that contained an unexpected material behavior, respectively (Fig. 3). Both classifiers successfully discriminated between the videos, for expected material behaviors from 130ms to 2,710ms (peak at 2,310ms, t[24]=7.4, d=1.5) and for unexpected material behaviors from 90ms to the end of the epoch (peak at 920ms, t[24]=12.1, d=2.4). Critically, we found enhanced decoding for the videos displaying unexpected material behaviors, compared to those displaying expected behaviors, from 900ms to 1,000ms (peak at 920ms, t[24]=5.1, d=1.0). This shows that already around 190ms after the material behavior is revealed (i.e., after the object hits the ground), there is a boost in cortical representations for the unexpected material behaviors. This enhancement may reflect additional processing demands when predictions about material behaviors are not met.

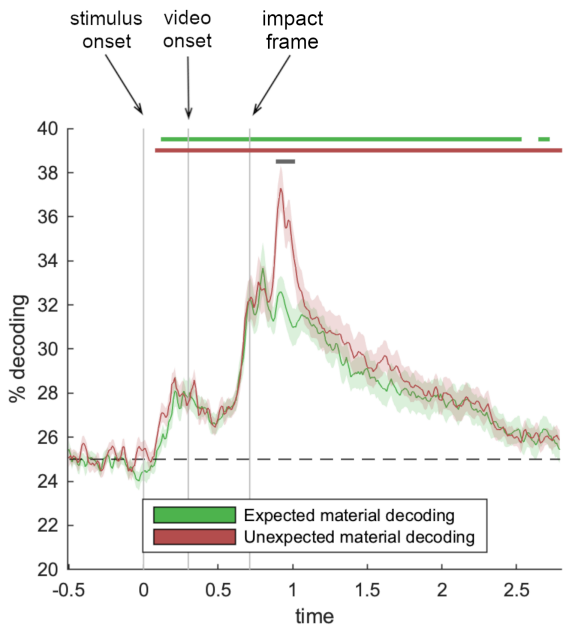

Figure 3. Enhanced representation of unexpected materials. *When comparing decoding for videos that displayed expected and unexpected material behaviors, we found enhanced representations of unexpected material behaviors that occurred around 190ms after the material was revealed (grey significance markers). Error margins represent standard errors of the mean. Significance markers denote p<0.05 (corrected for multiple comparisons across time).*

Expectation decoding

Finally, we asked whether there is a more general neural signal that indexes violations of material expectations that generalize across different objects and materials. Such a signal would indicate that there is a generic implementation of a prediction error that either triggers subsequent differences in visual processing or that, alternatively, follows from such differences. To answer this question, we trained classifiers on discriminating between all videos that contained an expected material behavior and all videos that contained an unexpected material behavior, in a two-way classification analysis (Fig. 4). These classifiers successfully discriminated between expected an unexpected videos from 220ms to the end of the epoch (peak at 1,020ms, t[24]=7.3, d=1.5). However, as these classifiers are again trained and tested on identical videos and thus can capitalize on pixel similarities in the train and test videos, we probed neural signals related to the fulfillment of expectations in a second analysis: Here, we trained classifiers on one combination of objects and materials (chair/milk – rigid/liquid) and tested them on another combination of objects and materials (custard/glass – wobbling/shattering), so that the classifiers could neither learn information about specific objects nor information about specific materials. In this analysis, we also found significant decoding of material expectations at multiple time points between 820ms and 1,300ms (peak at 1,130ms, t[24]=4.2, d=0.8). Interestingly, the first expectation-related decoding therefore occurred within 150ms after the impact frame, preceding the enhanced representation of unexpected material behaviors reported above. This pattern of results unveils a cascade of neural events, where an initial prediction error signal reflects a violation of expectation (indexing that the input does not match the expected visual pattern). This initial signal then triggers enhanced visual processing of unexpected material behaviors.

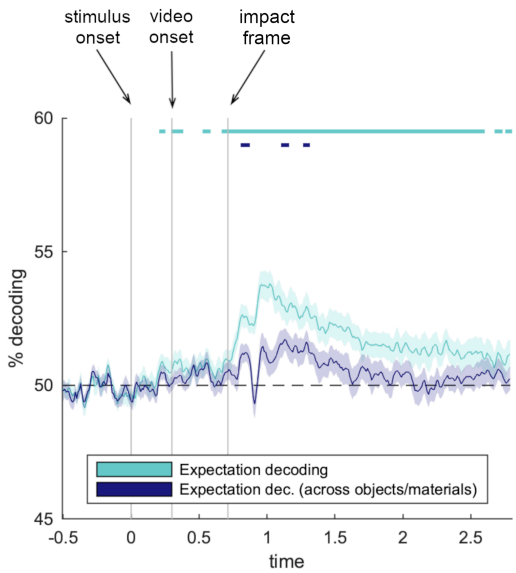

Figure 4. A general neural signal of expectation for material behaviors. *In a two way-decoding, we found that neural signals contained reliable information about whether the material behavior was expected or unexpected. Critically, when classifiers were trained and tested across different objects and materials, we still found an early, general signal reflecting participants' expectation for material behaviors, which occurred within 150ms of the object hitting the ground. Error margins represent standard errors of the mean. Significance markers denote p<0.05 (corrected for multiple comparisons across time).*

Discussion

Here, we used time-resolved EEG decoding to reveal the representation of expected and unexpected material behaviors in real-world objects. Our study yielded three key results: First, both objects and materials are represented in a temporally sustained fashion. Second, expected materials behaviors are represented more strongly than unexpected behaviors within 190ms after the impact. Third, general signals of expectation fulfillment that generalize across specific objects and materials are found within the first 150ms after the material is revealed. Together, our results provide new insights into the temporal neural processing cascade that underlies expectations for real-world object behaviors: When material behaviors are expected from an object's typical behavior in the world, the material is not strongly encoded in neural signals (indexed by decoding performance decreasing over time after the material is revealed). By contrast, when material behaviors are unexpected, material representations are enhanced (indexed by a boost in decoding performance after the material is revealed), reflecting the need for further visual analysis when the material behavior cannot be anticipated from the outset. This enhancement may be triggered by a general expectation-related signal that emerges rapidly, within 150ms after the material becomes apparent.

The early, general signal indexing fulfillment versus violation of expectation for material behaviors can be conceived as a neural prediction error (Rao & Ballard, 1999; Friston, 2005, 2010), where unmet expectations trigger error signals. The timing of this signal is consistent with prediction errors for expected simple stimuli and objects (Johnston et al., 2017; Robinson et al., 2018; Stefanics et al., 2015; Tang et al., 2018). Interestingly, Hoogendorn & Burkitt (2018) reported that neural signals at around 150ms post-stimulus signal the fulfillment of expectations about object movement trajectories. The early expectation-related signals observed in our study may reflect a similar mechanism, as an object's material was conveyed through different movement

patterns when hitting the ground. At this stage of processing, prediction errors in material perception may be triggered by predicted movement patterns: Already before impact, the brain may form expectations about the concerted transformation of low- and mid-level features on impact, which in turn leads to prediction errors that are similar across the individual objects exhibiting unexpected behaviors.

We show that this general signaling of fulfilled expectations is followed by stronger representation of objects exhibiting unexpected material behaviors from 190ms within the impact. In principle, this effect can be explained in two ways: First, there may be in increase in processing for unexpected material behaviors. Models of Bayesian inference (Kersten et al., 2004) predict that unmet expectations lead to recurrent updating of priors which requires additional processing of objects that exhibit unexpected material behaviors. Such recurrent prior updating can also explain delayed behavioral responses to unexpected material behaviors (Urgen & Boyaci 2022). Second, there may also be a decreased need for processing objects that exhibit expected material behaviors. When the material behavior can be expected, predictions can efficiently "explain away" the sensory input and further processing is eased (Friston, 2005, 2010). Although both mechanisms may play out concurrently, future studies could additionally use stimuli for which no expectations about material behavior are formed (such as meaningless shapes) to effectively dissociate the two mechanisms.

More generally, our study also provides new insights into the timing of material representations in the brain. In our study, robust material representations formed from 240ms after impact. This is considerably later than the representations observed in another EEG study on material perception from texture (Wiebel et al., 2014). This difference in timing may reflect differences between material perception from textures and movement. However, the later timing in our study is also attributable to our analysis scheme, in which we carefully probed material representations that generalize across objects, as well as across expected and unexpected material behaviors. It is worth noting that material representations may occur earlier than reported here when they are not probed across expected and unexpected cases. The exact timing of material representation thus requires further study.

In sum, we show that the neural representation of material behaviors is tightly linked to the expectations we form based on our real-world experience. Expected and unexpected material behaviors lead to differing representations across the visual processing cascade, with early signals reflecting a general signature of expectation fulfilment and later signals reflecting increased processing of unexpected, compared to expected material behaviors. The emergence of both these effects within the first 200ms of processing suggests that material representations are formed at fundamental stages of perceptual analysis.

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Declarations

The authors declare there are no conflicts of interest.

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