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Memorability shapes perceived time (and vice versa)

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Visual stimuli are known to vary in their perceived duration. Some visual stimuli are also known to linger for longer in memory. Yet, whether these two features of visual processing are linked is unknown. Despite early assumptions that time is an extracted or higher-order feature of perception, more recent work over the past two decades has demonstrated that timing may be instantiated within sensory modality circuits. A primary location for many of these studies is the visual system, where duration-sensitive responses have been demonstrated. Furthermore, visual stimulus features have been observed to shift perceived duration. These findings suggest that visual circuits mediate or construct perceived time. Here we present evidence across a series of experiments that perceived time is affected by the image properties of scene size, clutter and memorability. More specifically, we observe that scene size and memorability dilate time, whereas clutter contracts it. Furthermore, the durations of more memorable images are also perceived more precisely. Conversely, the longer the perceived duration of an image, the more memorable it is. To explain these findings, we applied a recurrent convolutional neural network model of the ventral visual system, in which images are progressively processed over time. We find that more memorable images are processed faster, and that this increase in processing speed predicts both the lengthening and the increased precision of perceived durations. These findings provide evidence for a link between image features, time perception and memory that can be further explored with models of visual processing.

Time is an intrinsic feature of sensory perception. Indeed, all sensory processes must unfold over time. Yet, 'time' in itself is a rarely studied feature of perceptual processing. That is, how do we perceive its passage, and how does its passage influence the processing of other features? This presents both a missing aspect of our models of neural functioning and an opportunity for future research: how is time instantiated within sensory processing hierarchies? Early research on the study of time focused on amodal properties of its perception; that is, the study of interval timing instead focused on time as a higher-order property of perception and cognition[1]. We focus our experiments here on the visual system, an area of strong interest for time perception[2].

Within psychology, the dominant model for studying time has been scalar expectancy theory[3], later expanded with the attentional gate model of time[4]. Both models assume a pacemaker-accumulator framework, in which clock-unit 'ticks' are accumulated until a given threshold. Critically, these models assume time as an amodal process, with no presumed differences across sensory modalities. Yet, despite the support of scalar expectancy theory and the attentional gate model for describing a variety of behavioural features of timing in humans and animals, work conducted throughout the 2000s and 2010s began to reveal perceptual biases that could not be explained by these models. Specifically, the sensory properties of timed stimuli altered their perceived duration. Early work in this regard demonstrated that the

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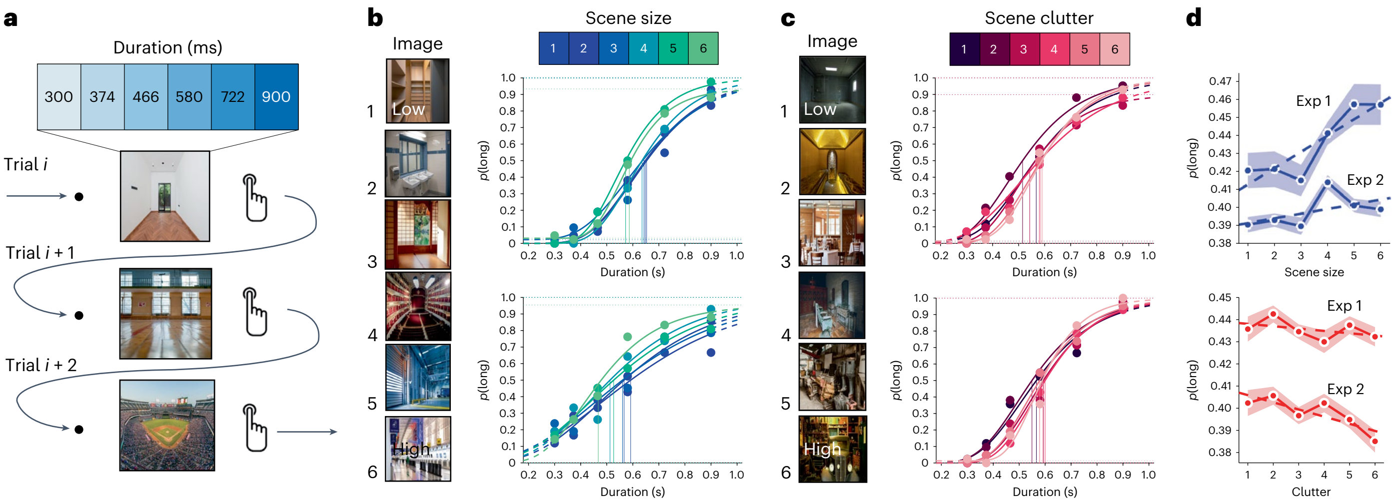

Fig. 1 | Scene information shifts perceived time. a, Schematic for the temporal categorization task. On a given trial (*i*), the participants viewed a fixation point followed by an image for one of six possible durations between 300 and 900 ms. After the image disappeared, the participants were required to classify the image duration as 'long' or 'short' as quickly yet as accurately as possible, after which the next trial (*i* + 1) began immediately. **b**, Scene size was varied across six levels and was observed to dilate perceived time, such that participants were more likely to categorize larger-scene-size images as 'long'. Example psychometric functions are presented for two participants from Experiments 1 (top) and 2 (bottom). **c**, Scene clutter was also varied across six levels and was observed to contract perceived time, such that participants were less likely to categorize more cluttered images as 'long'. Example psychometric curves from two participants are again presented for Experiments 1 (top) and 2 (bottom). The curves were fit using the psignifit v.4.0 toolbox and are presented here for visualization purposes only (see Supplementary Fig. 1 for average curves across participants). **d**, Average proportion of 'long' responses for scene size (top) and scene clutter (bottom) levels for both Experiments 1 ($n = 52$) and 2 ($n = 50$). Dashed lines represent a linear trend fit to the mean data. The data are presented as means ± within-participant standard errors in the shaded regions. Note that the images shown here are not those used in the actual study, which cannot be shown due to potential copyright; see Methods for links to the actual images. Photos from Pexels.com.

general magnitude of a stimulus influenced time in a linear manner: stimuli with 'larger' magnitudes, such as size, brightness, loudness, number, numerosity and speed, led to 'longer' perceived intervals (that is, time dilation[5]). A possible explanation for time dilation effects is that these stimuli drew more attention as a consequence of their magnitude[6], yet this explanation lacks validity in the attentional gate model, which predicts that such magnitudes would act as a distraction away from time and so should lead to opposite distortions (that is, time contraction). Explanations for these findings included a generalized 'magnitude' system in the brain[7], with time being just one aspect, and a basic 'energy-readout' model in which stimuli that elicited more activity led to longer intervals[8]. Yet, further studies revealed findings inconsistent with these accounts, in which time was dilated by other features, such as a visual stimulus's colour, flicker rate or spatial frequency, all of which were non-monotonic[9,10]. Furthermore, stimuli of lower magnitude could be perceived as longer if the context of an experiment was changed[11]. Inter-modal effects also existed, such that visual stimuli were generally perceived as briefer than auditory stimuli of the same duration[12]. 'Higher-order' visual stimuli also dilated time, including body motion (that is, upright human point-light walkers are perceived to last longer than inverted or scrambled walkers[13]), emotional content (that is, emotional faces and frightening images are longer than neutral faces and images[14]) and scenes (that is, images of scenes are perceived as longer than scrambled scenes[15]). For these latter stimuli, an important distinction is that it is their specific content, not their complexity, that dilates time; indeed, white noise patterns of differing complexity fail to have any impact on perceived duration[16].

Within sensory processing regimes, evidence has been found to support a visual representation of time. Neurons in area V1 modulate their firing rates in expectation of a temporally predictable stimulus[17,18], a finding observed in both humans and rodents[2,19]. Furthermore, the repetition of visual stimuli for the same duration can induce adaptation-level effects in their perceived duration[20], an effect linked to changes in visual cortex activation across the processing hierarchy[21–23]. Indeed, even auditory stimuli implying distinct object categories can evoke anticipatory activity in extrastriate regions[24]. Linking these findings to the time dilation effects described above, this suggests a hierarchy of time dilation effects across the visual cortex. That is, a variety of features from low to high level have been found to influence perceived duration. Yet, the majority of time dilation effects have involved lower levels of the hierarchy, manipulating simple features such as size, contrast and colour. Furthermore, many of these effects have favoured stimulus manipulations selective to the dorsal visual stream. Yet, stimuli putatively driven by the ventral stream can also dilate time[25], which may be driven by their semantic content rather than low-level sensory features[15,26]. However, previous research using high-level visual images[15,27,28] did not account for semantic properties.

One critical aspect of time dilation effects is that the dominant explanation for them is secondary in nature. That is, time dilation is the result of visual processing rather than a part to be incorporated in models of vision[29]. The alternative explanation is that sensory timing can be flexibly adapted to behaviourally relevant experience, such that stimuli that engender greater priority are processed quicker or more efficiently. One way of testing this possibility is to explore the timing of higher-level visual features that are ecologically relevant, including action, movement and memory.

Results

Perceived time is differentially influenced by scene size and clutter

To begin, we tested an initial group of human participants ($n = 52$) on a temporal categorization task (Fig. 1a), in which they were presented with images for a set of six possible durations on a given trial (log-spaced, between 300 and 900 ms) (Experiment 1). The participants were required to classify each presented image as 'long' or 'short' via a button-press as quickly yet as accurately as possible. We gave the participants no instructions regarding the images themselves, asking them only to attend to the durations they were presented. For this

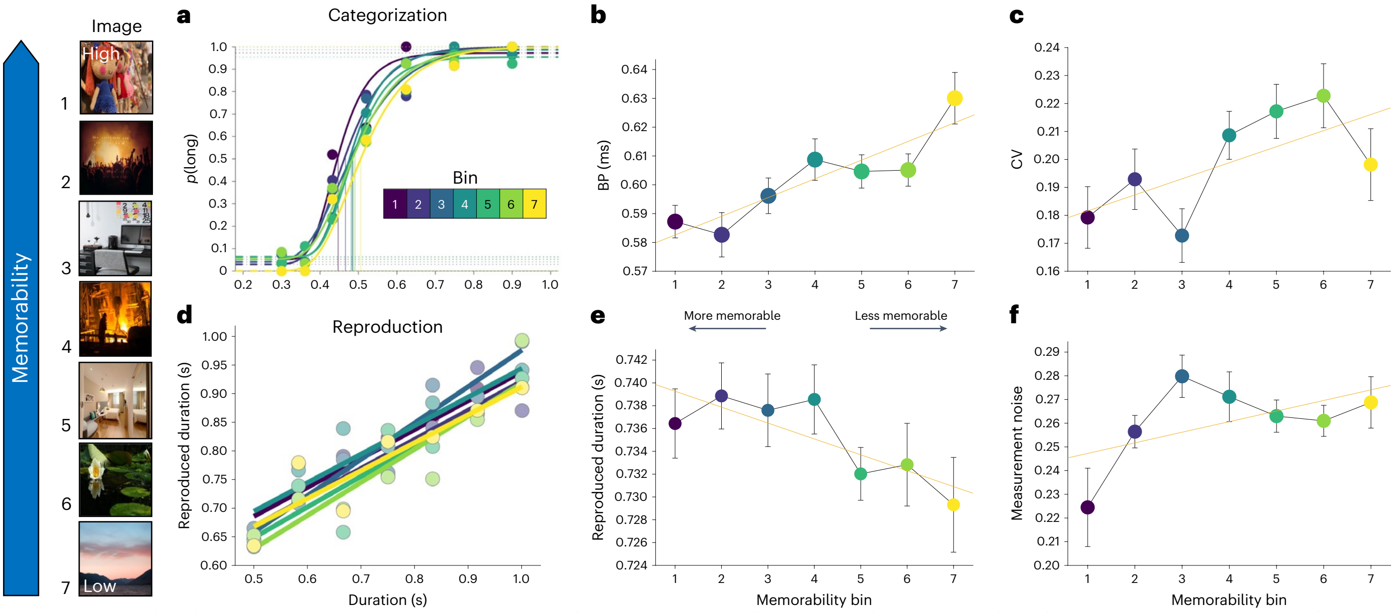

Fig. 2 | Memorability dilates perceived time. a–c, The participants ($n = 28$) were presented with stimuli drawn from the LaMem dataset that varied by their memorability ratings and were divided into a set of seven bins from low (7) to high (1). In a temporal categorization task (Experiment 3), participants were more likely to categorize images with higher memorability scores into the 'long' duration category. **a** displays psychometric functions from an example participant (see Supplementary Fig. 2 for average functions), whereas **b** displays average BPs across the seven memorability bins. Additionally, participants were more precise at categorizing the durations of images with higher memorability ratings, as evidenced by reduced CV values (**c**). **d**,**e**, In a temporal reproduction task (Experiment 4), participants ($n = 21$) reproduced longer durations after having encoded higher memorability images; the data from an example participant are shown in **d**, while **e** displays the average reproduced duration across memorability bins. **f**, Measurement noise as derived from a Bayesian observer model fit to participant responses, in which noise is additionally shown to be reduced for higher-memorability images. The data are presented as means ± within-participant standard errors; the yellow lines represent a simple linear fit. Note that the images shown here are not those used in the actual study, which cannot be shown due to potential copyright; see Methods for links to the actual images. Photos from Pexels.com.

experiment, the images we used were drawn from the Size/Clutter database built and described by Park et al.[30] (Methods). These images represent a series of scenes with normed responses across participants for ratings of scene size or clutter. For example, a scene with a small size but high clutter may be a full pantry, whereas a scene with a large size but low clutter may be an empty warehouse. The scenes were presented across six levels of size and clutter, for a total of 36 possible combinations (Fig. 1b). The data were analysed via a generalized linear mixed model (GLMM) approach in which the scene size and clutter levels, along with presented duration, were fixed effects and participant was a random effect. We observed an effect of both scene size and clutter, such that models with these terms outperformed models without them (scene size: $\chi^2_1 = 99.37$, $P < 0.001$; clutter: $\chi^2_1 = 5.94$, $P = 0.015$). The effects worked in opposite directions: larger scene size led participants to categorize stimuli as 'long' more often ($\beta = 0.055$; 95% confidence interval (CI), 0.044–0.065), whereas more clutter led them to categorize stimuli as 'short' more often ($\beta = -0.044$; 95% CI, −0.079 to −0.008) (Fig. 1b). Additionally, we observed an interaction between presented duration and clutter ($\chi^2_1 = 4.772$, $P = 0.029$). Notably, the slope of this interaction was positive ($\beta = 0.067$; 95% CI, 0.006–0.127), such that the slope of the psychometric function was higher for larger levels of clutter[31]; thus, despite the bias to classify the duration of more cluttered images as 'short', participants were more precise in their classifications. No such interaction was observed for scene size.

The results of the first experiment thus showed that scene size and clutter could push perceived duration in two separate directions. We note that this finding goes against a simple attentional explanation, unless one were to suggest a more complicated explanation that scene sizes draw more attention than scene clutter, which decreases attention with greater clutter. Likewise, a simple magnitude-based effect cannot explain these findings, as both scene size and clutter are larger magnitudes. To further validate these effects, we collected a replication dataset in a new group of participants ($n = 50$; Experiment 2). As an additional control, the images presented were set to greyscale and normalized for luminance (Methods), to ensure that the results were not due to low-level differences in the intensity of the image. Once again, we observed a significant effect of including both scene size ($\chi^2_1 = 9.497$, $P = 0.002$) and clutter ($\chi^2_1 = 8.6$, $P = 0.003$) in our model, with larger scene size pushing stimuli to be classified as 'long' more often ($\beta = 0.017$; 95% CI, 0.005–0.028) and more clutter pushing stimuli to be classified as 'short' more often ($\beta = -0.018$; 95% CI, −0.029 to −0.006). However, a model including an interaction between duration and clutter did not significantly improve the fit ($\chi^2_1 = 0.047$, $P = 0.826$), thus failing to replicate the effect of clutter on precision. Between experiments, we noted a tendency for participants to classify stimuli as 'long' more often in Experiment 1 than in Experiment 2 (Fig. 1d); however, a combined analysis of both datasets found no effect of adding experimental group to the model ($\chi^2_1 = 2.13$, $P = 0.144$).

Memorability lengthens perceived time

The results of the first two experiments demonstrated that semantic details of scenes can shift perceived time in different directions, depending on the type of information conveyed. These findings could not be explained by simple magnitude or attention-based theories, or by differences in low-level features of the images. So, why do these images affect time in different ways? We return to this question in the Discussion but note that the richness of scene images provides a number of distinct cues, many of which are perceived immediately. Beyond features such as size or clutter, an additional feature of images is their intrinsic memorability, or the probability that they will be recalled later[32,33]. Numerous studies have investigated features that give rise to memorability, noting that it is a unique property of images that operates independent of attention[33]. One possibility, then, is that memorability affects perceived time[34]. To explore this possibility, we conducted a third experiment on a new set of participants, in which the participants categorized the duration of images that varied according to their memorability ratings (Experiment 3). We used seven log-spaced durations between 300 and 900 ms for this experiment, providing better characterization of the psychometric function. The images were uniformly drawn from the Large-Scale Image Memorability dataset (LaMem; Methods), a large collection of images tested for recognition accuracy. We sampled images across all memorability scores and divided them into seven equally spaced bins from high (1) to low (7) in memorability ratings (Fig. 2a).

Psychometric functions were constructed for the response proportions for each tested duration, from which the bisection point (BP), defined as the duration at which participants were equally likely to classify the interval as 'long' or 'short', and the coefficient of variation (CV), defined as half the difference between the upper and lower thresholds divided by the BP, were calculated (Methods). These measures were calculated to retrieve an individual measure of bias (the BP) and precision (CV). Accordingly, the BP reflects the subjective 'middle' duration of the distribution, such that a lower BP value reflects a greater tendency to classify stimuli as 'long', whereas the CV reflects the normalized steepness of the psychometric function, such that a lower CV indicates a clearer division when judging stimuli. A repeated-measures analysis of variance of BP values found a significant effect of memorability ($F_{6,150} = 3.467$, $P = 0.003$, partial eta-squared (η^2_{p}) = 0.122), which was observed to be significantly linear in nature such that participants were more likely to classify intervals as 'long' for more memorable images (two-tailed $t_{150} = 3.827$, $P < 0.001$) (Fig. 2a,b). Surprisingly, for the CV, we also detected a significant effect of memorability ($F_{3.738,97.99} = 2.653$, $P = 0.041$, $\eta^2_{\mathrm{p}} = 0.093$) that was also significantly linear in nature, such that more memorable images were also classified with better precision (two-tailed $t_{156} = 2.643$, $P = 0.009$) (Fig. 2c).

Perceived time increases memorability

The results of Experiment 3 demonstrated that more memorable images are perceived both as longer than less memorable ones and more precisely. That is, an intrinsic aspect of these images that allows them to be better recalled is also responsible for dilating the duration that they are presented for. Yet, this relationship is correlational, and so the directionality of the effect is unknown (Fig. 3a). To pose the question clearly: do these images last longer because they are more memorable, or are they more memorable because they last longer? Previous research has shown that the duration for which an image is objectively presented increases the likelihood that it will be remembered[35–37], yet whether a subjectively longer image is thus recalled better is not known. Evidence of such a relationship would differ from a magnitude-based explanation; for example, larger stimuli are commonly perceived as lasting longer, but presenting a stimulus for a longer duration does not make it appear larger.

To test this hypothesis, we had a new set of participants perform a temporal reproduction task (Experiment 4) using the same memorability images from Experiment 3 (Fig. 3a). In this task, the participants were presented with images from the memorability image set for a range of seven linearly spaced intervals between 500 and 1,000 ms and then required to reproduce that interval by pressing and holding a response key for the same interval. We chose a reproduction task here for two reasons: (1) to replicate the findings of Experiment 3 but in a different task and (2) to obtain a continuous, rather than categorical, estimate of perceived duration. The result of this initial task replicated the findings of Experiment 3; a linear mixed model (LMM) of reproduced durations was significantly improved by adding the memorability score of the image ($F_{1,3509} = 9.697$, $P = 0.002$), with higher memorability scores associated with longer duration estimates ($\beta = 0.029$; 95% CI, 0.011–0.048). As an additional measure, we decomposed reproduced duration estimates with a Bayesian observer model, in which the measurements of durations on each trial are conceived as draws from a noisy Gaussian distribution that scales with the interval duration. These estimates are then combined optimally with a uniform prior distribution of presented durations to form a posterior estimate, which is then further corrupted by motor production noise in the reproduction phase[38–41]. Fitting this model to single-trial responses yields an estimate of both the measurement and production noise widths. We observed that the measurement noise decreased for images from higher memorability bins ($F_{3.804,68.476} = 2.611$, $P = 0.045$, $\eta^2_{\mathrm{p}} = 0.127$; Greenhouse–Geiser corrected) in a linear manner (two-tailed $t_{108} = 2.163$, $P = 0.033$), while no effect was found for production noise ($F_{4.728,\,89.829} = 0.465$, $P = 0.791$). Thus, a similar effect of memorability on the CV of Experiment 3 was observed for the measurement error of Experiment 4.

Following the reproduction tasks, all participants returned a day later for a second session, in which they were presented with a surprise memory test (Fig. 3a). In this phase, the participants were presented with the same 196 images from the previous day, along with a new set of 196 image foils drawn from the same memorability bins as the first set. The participants were presented with each image and asked to judge whether they had seen it on the previous day. A GLMM analysis of accuracy scores in this task for each image replicated the well-known effect of memorability ($\chi^2_1 = 684.966$, $P < 0.001$), with higher memorability scores associated with a greater probability of recall ($\beta = 4.977$; 95% CI, 4.567–5.386). Crucially, the inclusion of average reproduced duration from the previous day's session also improved model fit ($\chi^2_1 = 4.43$, $P = 0.035$), with longer reproduced durations associated with greater recall ($\beta = 0.635$; 95% CI, 0.049–1.221). This model also outperformed one with only reproduced duration ($\chi^2_1 = 684.97$, $P < 0.001$). We note that the intervals used represented the average across all objectively presented durations for each image (Methods). An interaction between memorability and reproduced duration did not significantly improve the fit and so was not warranted ($\chi^2_1 = 2.31$, $P = 0.129$) (Fig. 3c). Inspection of predicted model fits additionally yielded an unexpected finding: while longer duration estimates were associated with better recall, those participants who overall reproduced longer durations were less likely to recall images in general. This finding, an example of Simpson's paradox, was evident when removing participant as a random effect, which thus changed the β estimate for duration from a positive value to a negative one ($\beta = -0.543$; 95% CI, −0.827 to −0259). One possible explanation for this effect is that participants who reproduced longer durations overall were attending less to the images and more to the passage of time. Indeed, greater attention to time typically leads to both longer estimates and more precise ones[42]. In support of this, we observed a significant between-participant correlation between average reproduced duration length and average precision, as indexed by the CV (Spearman's ρ, −0.6234; $P = 0.0031$), such that participants who reproduced longer intervals also reproduced them more precisely. It is therefore possible that participants who were more effectively able to ignore the images, and so reproduce longer duration estimates, were thus less effective at encoding the images into memory, an effect that future work will need to investigate further; nonetheless, these same participants were still affected by the intrinsic memorability of those images, such that more memorable ones and those reproduced as relatively longer were relatively better remembered.

As an alternative analysis, we median-split individual participant reproduced durations for each memorability bin into relatively 'short' and 'long' durations and then examined the probability of recalling an image for each bin and duration length (Fig. 3d). In addition to a significant effect of memorability bin ($F_{6,120} = 111.347$, $P < 0.001$, $\eta^2_{\mathrm{p}} = 0.848$), we observed a significant effect of reproduced duration from the previous day ($F_{1,20} = 9.875$, $P = 0.005$, $\eta^2_{\mathrm{p}} = 331$), with no interaction between the two ($F_{6,120} = 1.737$, $P = 0.118$). Across memorability bins, longer reproduced durations within participants and within memorability bins were associated with significantly improved recall (two-tailed $t_{17} = 3.142$, $P = 0.005$, Cohen's $D = 0.686$).

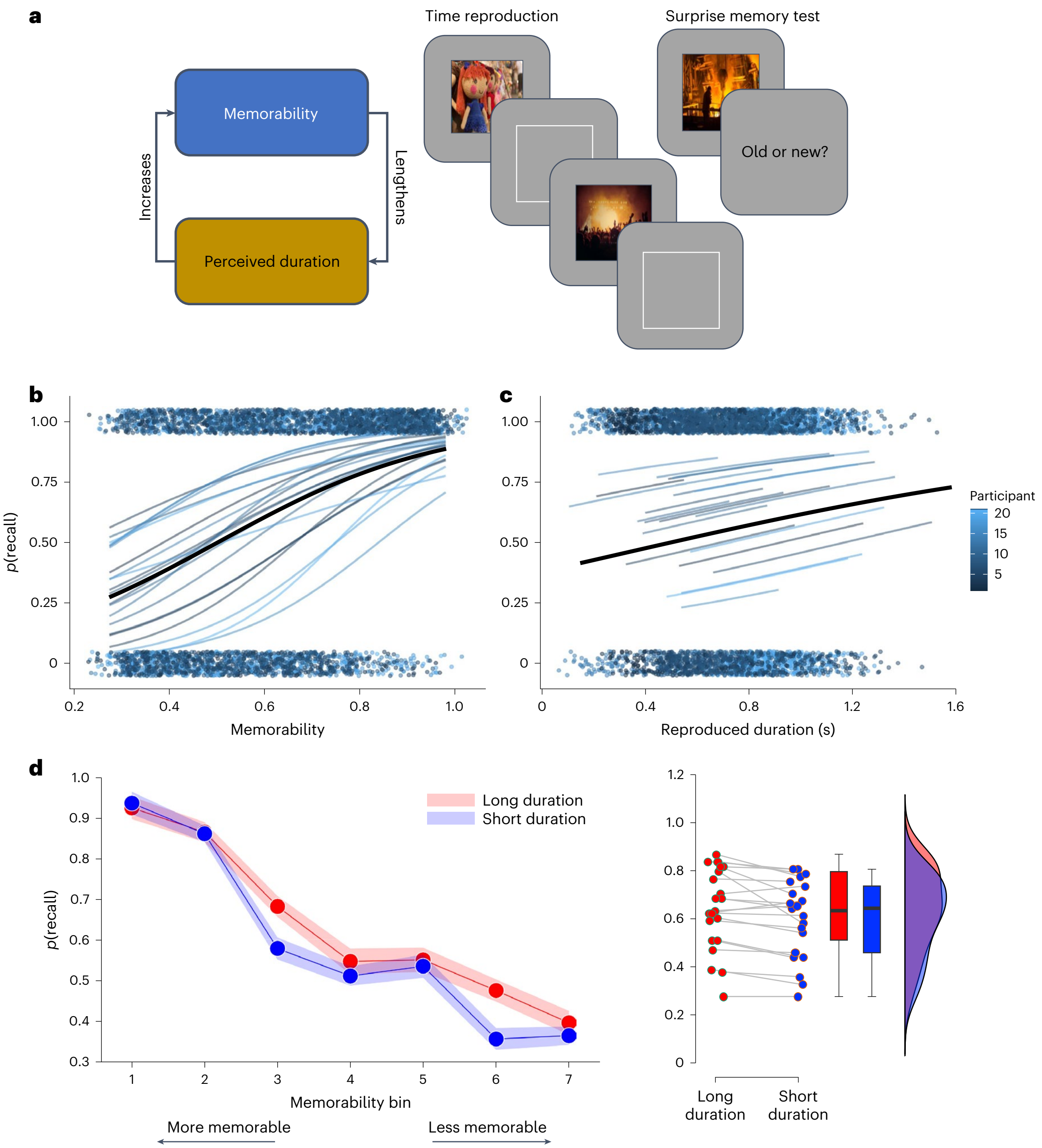

Fig. 3 | Perceived duration affects memorability. a, Proposed bidirectional relationship between memorability and perceived duration, such that greater memorability of stimuli lengthens their perceived durations, but longer durations also increase the likelihood of remembering a stimulus. To test this, participants (*n* = 21) performed a time reproduction task with memorability stimuli and then performed a surprise memory test on a subsequent day in which they recalled stimuli from the previous day. **b**, Regression estimates for single participants and the group average (black line) between the memorability of presented images and recall performance, demonstrating greater probability of recall for more memorable images. **c**, Regression estimates for average reproduced duration estimates for individual images and recall performance, demonstrating greater probability of recall for longer reproduced durations. The individual data points represent single-trial responses for each participant. **d**, A separate analysis, in which recall accuracy on the memory test was median-split by the reproduced duration on the previous day, for each participant, into short and long duration groups. Recall was higher within participants and within each memorability bin when the reproduced duration was longer. The data are presented as means ± within-participant standard errors in the shaded regions. The right panel displays a raincloud plot of the change in recall, collapsed across memorability bins. In the box plots, the centre line indicates the median, the box edges indicate the interquartile range and the whiskers extend to the maximum and minimum; the distributions represent kernel density estimates. Note that the images shown here are not those used in the actual study, which cannot be shown due to potential copyright; see Methods for links to the actual images. Photos from Pexels.com.

Neural network modelling

How can we explain the effect of memorability on time? We assert that appeals to other perceptual phenomena such as attention or magnitude are insufficient to explain this link. Memorability draws on a variety of details that give rise to its effect[43]; furthermore, memorable images exist independent of attentional effects[44,45], and one would not judge that a more memorable image is higher along an axis of magnitude such as size or quantity. To explain these findings, we turned to

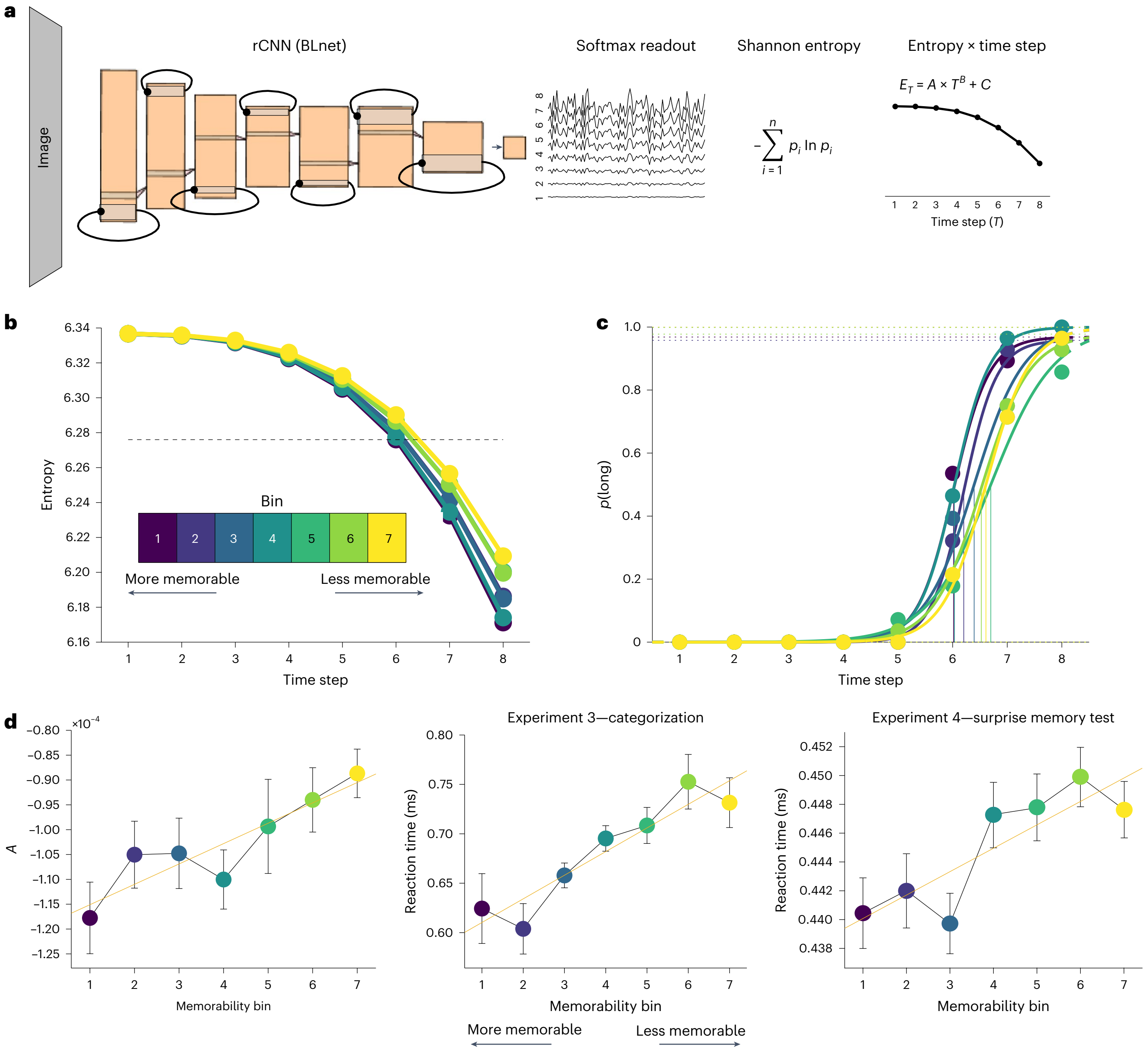

Fig. 4 | Neural network modelling of memorability and time. a, Schematic layers used for an rCNN, BLnet. Images are fed and processed across the network in a feedforward manner but with lateral recurrent steps for each layer, such that the input to each layer is refined at successive steps. At the final layer, a softmax readout provides classification probabilities for each time step (eight time steps are used). For each readout, Shannon entropy is calculated, resulting in a time series of entropy values, which are then fit with a simple, two-parameter power curve. **b**, The memorability images used in Experiments 3 and 4 were fed into BLnet, from which entropy values were averaged across each memorability bin, thus revealing that images with higher memorabilities exhibited faster reductions in entropy. Setting a threshold on these entropy values allowed us to construct a psychometric function for categorizing time intervals (for arbitrary time steps) as short or long. The dashed line represents the entropy threshold after fitting the model to human participant choices. **c**, The resulting psychometric functions for the entropy threshold and for each memorability bin. The psychometric data recapitulated both the time dilation effect for more memorable images and the increase in precision. **d**, The left panel displays the average value of the *A* parameter from the simple power curve model; low values represent faster rates of decrease in entropy. The middle and right panels display the average reaction time data from Experiment 3 and the surprise memory test portion of Experiment 4, both of which exhibit faster reaction times for more memorable images. The data are presented as means ± within-participant standard errors.

computational models of vision. In particular, convolutional neural network (CNN) models have been a major tool for vision researchers to measure links between activation 'layers' and corresponding components of the ventral visual stream[46,47]. Indeed, CNNs and other model developments (that is, ResNets) have been quite successful at estimating memorability and linking it to particular image features at a variety of levels of the hierarchy[32,48]. But CNNs as a base model cannot provide a strong explanation for our findings, as these models do not operate over time. A recent advance in CNN models, however, is to add feedback connections within and between layers, thus generating recurrent CNN models (rCNN). In these models, the outputs of individual layers can be 'unrolled' across successive time steps as recurrent, feedforward and feedback connections[49]. This process thus provides a timescale by which an input can be successively processed. We note, however, that the step distance in this case is arbitrary; that is, one can appeal to conduction delays between layers, but without neural data to corroborate the difference between 'engineering' time and 'biological' time, this is irrelevant[50].

To investigate how computational models of vision might explain our findings, we turned to an rCNN model known as BLnet (Bottom-Up Lateral Network), containing seven layers and recurrent connections within each layer. We chose this network because it provides a built-in series of time steps (eight) for processing an image, in which a readout is provided with each time step, but more importantly because the output of this network has been shown to correlate with human reaction times for image classification[50,51] as well as rapid object recognition[52]. This is achieved by extracting the softmax readout at each of the eight time steps and then calculating the entropy of each readout. As the model will converge on a set of image categories over others with repeated recurrent steps, the entropy of the softmax distribution will decrease with successive time steps (Fig. 4a). By selecting a threshold for entropy, one can infer the model's 'reaction time' to a particular stimulus.

To begin, we fed the 196 images presented to the participants in Experiments 3 and 4 into BLnet and calculated the entropy across the eight time steps. These responses were then binned by their memorability ratings. As in previous studies, we observed that the entropy decreased across time steps. Notably, we found that the rate of decrease could be modelled with a simple power curve model (Methods), which fit the data extremely well (mean $R^2 = 0.99$). We also observed that memorability affected the rate of this decrease, such that entropy for more memorable images decreased at a faster rate than that for less memorable ones (time step × memorability interaction: $F_{1,194} = 4.487$, $P = 0.035$) (Fig. 4b), which was captured well by a linear effect of the A parameter of the simple power curve model (two-tailed $t_{162} = 2.887$, $P = 0.004$) (Fig. 4d). An interpretation of this finding is that images that are more memorable are processed faster than those that are less memorable[44], with the network converging on a set of categorizations more consistently over time. In support of this notion, we returned to the results of Experiment 3 (temporal categorization) and the surprise memory test of Experiment 4 and analysed reaction time as a function of memorability bin (Fig. 4d). For both experiments, we observed faster reaction times when responding to stimuli from higher memorability bins (Experiment 3: $F_{6,162} = 2.851$, $P = 0.011$, $\eta^2_p = 0.096$; Experiment 4: $F_{6,120} = 4.634$, $P < 0.001$, $\eta^2_p = 0.188$). Both results are somewhat surprising; for temporal categorization, one might expect more memorable images to take longer to respond to, as the participants were not required to process anything about the images but instead had to render a judgement on their duration. For the surprise memory test, the participants were not given any instruction to speed their responses but nonetheless responded quicker for progressively more memorable stimuli. One possibility, then, is that longer perceived durations are the result of this faster speed with which the network operates on more memorable images. To determine whether this was the case, we set an entropy threshold; for each time step and each image, an entropy value above this threshold would categorize the stimulus as 'short', and a value below it would categorize the stimulus as 'long'. The average proportion of 'long' responses was then calculated for each memorability bin, thus providing seven psychometric functions, which were fit in the same manner as Experiment 3 (Methods). We then fit these functions to the subject data by finding the entropy threshold that provided the best match for both the bias and precision effects we observed.

The results of the above analysis revealed that the model recapitulated both of the observed effects in humans, with higher-memorability images having a greater probability of being categorized as 'long' and also a steeper—more precise—psychometric function (Fig. 4c). To the former effect, longer perceived durations were a direct result of the faster speed with which the network converged on a solution, such that the entropy threshold was hit earlier in time. To the latter effect, the increase in precision was also due to the speed at which the network converged, such that a smaller proportion of the range of possible entropy values for a more memorable image overlapped with the entropy threshold (see Supplementary Figs. 3 and 4 for simulations), an observation that we note is similar to accumulator-based models of time perception[12].

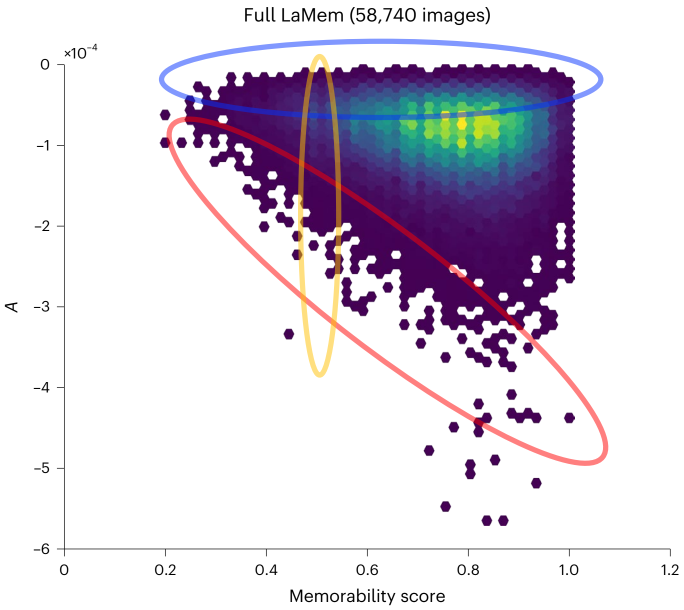

Fig. 5 | Density scatter plot of memorability scores against the simple power curve model *A* parameter for all images in the LaMem dataset. A significant relationship was observed similar to the sample images used in Experiments 3 and 4, with more memorable images characterized by a faster rate of entropy decrease. Hexagon colors reflect the density of data points at that location. The ellipses represent three axes along which images could be sampled with differing predictions for perceived memorability or time. The blue ellipse indicates those predicted to increase in memorability but with no change in perceived duration (the entropy decrease is approximately the same for all images). The red ellipse indicates those predicted to increase in both memorability and perceived duration. The orange ellipse indicates images that all have the same memorability score (0.5), but with progressively faster decreases in entropy and so longer predicted durations. See Methods for links to all images and their associated scores.

To extend the results of our analysis of memorability, we applied our rCNN analysis to the entire corpus of the LaMem dataset, comprising 58,740 images. We again calculated entropy time courses and fit them with our simple power curve model, from which the A parameter was extracted. We observed a significant correlation between the rate of entropy decrease and image memorability in the same direction as for our sample of 196 images (Spearman's ρ, −0.1134; $P < 0.001$); we note that the noise ceiling within-dataset rank correlation is 0.77 (ref. 32). Closer examination of the scatter plot of the relationship revealed that entropy decreases varied widely across images of different memorabilities (Fig. 5). Assuming that the rate of entropy decrease predicts time dilation, one can make predictions regarding which stimuli in the LaMem dataset will lengthen duration estimates and which will not (Fig. 5). Qualitative examination of some of these images reveals that those predicted to increase memorability, but not time, exhibit little variation in content and notably lack discernible objects. In contrast, those that dilate time, but with no difference in memorability, appear to contain more low-level feature differences. We provide these data to the wider community for further examination and to test their predictions (see 'Data availability').

Discussion

The results of the preceding experiments demonstrate that higher-order semantic features of scenes can shape perceived time. These features include aspects of scenes relevant for navigation, including scene clutter and size, as well as the intrinsic feature of image memorability. Furthermore, the results show that this effect is bidirectional: changes in perceived time have relevance to the perception of those stimuli themselves, such that subjectively longer perceived intervals are more likely to be recalled. These effects point to a series of loci along the ventral visual stream for compressing and dilating subjective time. Combined with our application of a model of the visual system, these effects suggest that the changes in perceived time are the result of processing efficiency for those natural images, which occurs as a result of recurrent feedback connections within visual circuits.

Scene features and perceived time

The first two experiments demonstrated opposite directions of the effects of the image scene qualities of size and clutter on perceived time, such that the former dilates and the latter compresses perceived time. These findings stand in opposition to a number of explanations for time dilation phenomena. For example, magnitude accounts would predict that both scene size and clutter should produce time dilation effects. Indeed, the perception of clutter is akin to that of numerosity, where time dilation effects have been observed in response to large dot arrays[53]. Likewise, appeals to increases in arousal, attention or neural response to the stimuli would all suggest that both scene size and clutter should increase perceived duration[5]. The most similar finding to the present one is a brief report noting that paintings of increasing complexity, defined using low-level features such as edges and contrast, also lead to time compression[27]; yet this study presented images for very long intervals (~30–60 s), whereas the present study employed very brief durations all less than one second. One possibility may relate to the stability of these images across the visual hierarchy. Indeed, while scene clutter is known to peak earlier in the decodability of neural responses than scene size, it has also been shown that increases in clutter impair object recognition[54], which may relate to how consistent these representations are in visual responses[30,55,56]. Recent work has also shown that increases in the objective time of presented images lead to more stable representations, rather than extended firing rates, in higher-level parts of the ventral stream[57].

A second possibility for explaining the size/clutter effects relates to their action affordance. That is, the clutter and size of a scene are both relevant features for navigation and movement[58], and recent work has shown that humans extract information about a presented scene in a way that supports their movement through that space[59]. Indeed, prior work has also demonstrated differentiated neural representations for scenes depending on whether the objects presented in that scene are reachable or not[60]. Increases in the size of a scene would suggest a longer necessary path to traverse the space presented, and previous work has shown that larger presented distances dilate perceived time[61]. Similarly, a more cluttered scene would suggest more difficulty in reaching one's goal. One possibility, then, is that scenes were judged in terms of path length, with cluttered scenes implying a longer length; this explanation would support a magnitude-based explanation for both scene size and clutter, yet it suggests that both local and global image features are integrated at distinct levels for influencing perceived duration. In relation to the memorability findings of the present study, we note that scene clutter has been linked to lower memorability[62,63]. However, we do not suggest that the size/clutter effects are driven solely by memorability, although it is possible that memorability played a role.

Memorability and perceived time

The last two experiments demonstrated that the memorability of a scene dilates the perceived duration for which it was presented. Likewise, increases in the perceived duration of a scene increase its memorability. These findings go beyond a simple unidirectional explanation, in which the perceptual feature affects its perceived duration as a by-product of its processing. Indeed, memorability has been demonstrated as a perceptual feature of a stimulus related to processing in higher regions of the ventral stream such as the inferotemporal cortex[33,64]. Similar to our findings, recent work has shown that increasing either the objective or subjective size of an image also increases its memorability[65,66]. These findings are suggested to relate to the size and spread of activation resulting from larger images on the surface of striate and extrastriate regions[67]. Longer objective durations are also known to increase the memorability of an image[35–37]. Yet, in our findings, we also observed that the durations of more memorable images were perceived with greater precision. That is, the duration of a more memorable image was perceived both as longer and with more consistency from trial to trial. This second finding sets memorability effects apart from other time dilation effects, which commonly do not change precision, but also points to differences in the stability of the neural representation.

The finding that memorability and time both affect one another suggests a single underlying factor driving both effects. Yet, more generally, why should time dilation effects occur at all? Until now, the dominant framework has asserted that time dilation results from increases in attention or population neuronal responses. Either case relies on a more-is-more connection, where increases in attention or firing rate lead to longer perceived durations. Crucially, there is a directional link to this framework, where time dilation is a consequence of increased neuronal firing, rather than a cause. The result is that time dilation is an epiphenomenon operating downstream from neuronal computations for stimulus coding[21]. However, an alternative framework that we propose here is that time dilation effects may instead serve a purpose for the visual system. Under this new framework, we propose that time in the brain serves as an information seeking strategy[5]. This new framework connects to the recent notion of priority coding in the visual system[68], wherein stimuli are processed according to the priority they engender (for example, threatening, emotional, rewarding or appetitive). Yet, under the priority coding framework, the processing of visual stimuli is limited by an information bottleneck that is time-limited (that is, only so much information can be processed at once[69]). To surmount this, we suggest that the information bottleneck can be dynamically changed to accommodate higher-priority stimuli. In this way, time is dilated or compressed to increase the amount of information that can be processed in any given instance, and so time is not epiphenomenal but central to population coding. We note that versions of an adaptive temporal window have been proposed before (for example, refs. 70,71) but not comprehensively explored across the visual hierarchy.

The notion of changes in information processing related to time has other experimental evidence to support it. For example, humans are able to adjust the rate of evidence accumulation to the rate of stimulus presentations in a dynamic environment[72]. Likewise, recent work has shown that humans can vary the encoding speed of visual items in working memory, depending on the duration at which items are presented[73]. These findings provide further support to the notion that time is a controllable feature of visual processing. In support of this, our application of an rCNN model provides an avenue by which time dilation effects may occur. In this model, the responses at each layer are fed both forward to subsequent layers and laterally back to themselves. This process, in which a CNN is 'unrolled' in time, allows for image processing to occur across multiple time steps[50,74], which are meant to mimic the feedforward 'sweep' of the visual hierarchy as well as recurrent connections[49,75]. Critically, for image processing, this allows image representations to be refined over time as the model converges on a set of solutions (that is, the probability distribution of object identities). Here we observed that more memorable images were processed faster across successive time steps in the rCNN, such that the probability distribution converged earlier in time. By applying a threshold to the time series and using this to mimic the decision process in a categorization task, we found that the model could replicate both the time dilation and precision effects observed in behaviour for memorability. Time dilation thus results from a faster speed of the network rather than an increase in neural firing; likewise, faster speeds are associated with less variability, and so this leads to greater precision for categorizing time intervals. This finding mirrors recent neural recordings in non-human primates, as well as modelling with RNNs, demonstrating that perceived duration is the result of changes in the speed of neural trajectories through state space[76–78]. However, whether time dilation effects in general are an effect of changes in speed in neural trajectories is unknown and would need to be tested in biological networks. In our case, the change in speed is the result of changes in processing across layers of the ventral stream rather than within any given region, a finding that will need to be tested experimentally.

Yet, the question remains: why should more memorable images be associated with a faster speed in the network? The question gets at the heart of what makes an image memorable to begin with, on which considerable work has been done[33,43,79], finding that memorability results from both low- and high-level features[80,81]. Here, the behavioural and network findings support the notion of an increase in processing efficiency for memorable images[82]. One possible driver of this efficiency may relate to object properties within these images, as recent work has shown that image memorability is partially determined by the typicality of objects contained within them[83]. Notably, the rCNN model here was originally trained for object classification. One possibility, then, is that model speed (and memorability) is determined by how similar objects in the presented image are to the categories on which it was trained; likewise, speed effects will also depend on the images on which the model has been trained[84]. The creation and curation of more complex memorability datasets with ground-truth categories thus allow us to test for this possibility[83,85].

Conclusion

The results of the experiments outlined here provide evidence for a link between the perception of time and the semantic features of scenes. Furthermore, they indicate a bidirectional effect between memorability and perceived duration. These results point to a framework in which time dilation is both the result and the cause of priority coding in the visual system, which is verified by computational modelling of the ventral visual stream. We suggest that a large variety of visual stimuli may be used to explore timing responses across different levels of the hierarchy, including those associated with reachable objects, animacy, sizes, textures, metamers and forms, all of which can provide insight into the location of time dilation effects across the visual system.

Methods

Participants

A total of 170 participants (59% female, 25% male and 16% not declared) took part in the four experiments described in this study. No participants participated in more than one experiment. All participants were drawn from the undergraduate pool of George Mason University and took part for course credit. All experiments were conducted at George Mason University, with all protocols approved by the Institutional Review Board (IRB approval no. 1867674-1). All participants provided informed consent for participating. Experiments 1–3 were run online during the COVID-19 pandemic, whereas Experiment 4 was run in person after pandemic protocols had been eased for data collection. All participants were right-handed and neurologically healthy with normal or corrected-to-normal vision. Experiment 1 included 52 participants (mean age, 20.5; s.d., 5.6), Experiment 2 included 50 participants (mean age, 21; s.d., 4.8), Experiment 3 included 48 participants (mean age, 20.3; s.d., 2.5) and Experiment 4 included 21 participants (mean age, 21.2; s.d., 3.66). All experiments were programmed using Psychopy (version 2020 and above) in the Python programming language (www.psychopy.org). The online experiments were conducted using the Pavlovia platform (www.pavlovia.org). The in-person experiments were conducted in a testing room with stimuli presented on a 100 Hz Dell Gaming Monitor and responses collected on a Corsair MX Gaming Keyboard with a 1,000 Hz polling rate. For all experiments, the participants were not informed of the nature of the images they were presented, and they were not given any instructions related to their processing; rather, the participants were only told to attend to the duration for which the images were presented, regardless of their content.

Experiments 1 and 2: temporal categorization of scene size and clutter

Procedure. All participants performed a visual temporal categorization task (also referred to as a time bisection task) with sub-second stimuli. The stimuli consisted of images drawn from the Size/Clutter database of ref. 30, which is available at https://konklab.fas.harvard.edu/#. A total of 252 images were chosen from across the dataset, which spans six levels of size and clutter based on participant ratings. For Experiment 1, we used the images as provided from the Size/Clutter database; for Experiment 2, all images were processed via the SHINE toolbox[86], in which the images were turned to greyscale and normalized for luminance. At the start of each trial, the participants were presented with a fixation point that appeared at the centre of the screen for 500 ms, and then a visual stimulus was immediately presented. The stimulus order was randomized for each trial, and images appeared for one of six logarithmically spaced time intervals ranging from 300 to 900 ms. Logarithmic spacing allows for more supra-geometric spread when visualizing the data[87]. Accordingly, each image was presented once for each of the six possible durations, leading to a total of 1,512 trials in a given session. A break was implemented every 168 trials, which participants could end by pressing a response key. The image size was set to $(0.5)^2$ times the height of the monitor, following recommendations for presenting stimuli for online experiments to account for differing screen sizes across participants. On a given trial, the participants were tasked with judging whether the stimulus presented was ‘short’ or ‘long’ on the basis of their subjective threshold of the durations. They were directed to respond as quickly and accurately as possible using the ‘s’ key for ‘short’ and the ‘l’ key for ‘long’. There was no response screen following the stimulus; the participants were simply instructed to answer as soon as the image disappeared. They did not receive feedback during this task, and the next trial began upon their response.

Analysis. Participant responses were entered in a GLMM, with stimulus duration and the magnitude of the size or clutter of each image as fixed effects and participant as a random effect[31]. We chose a GLMM analysis due to the large number of factors and levels, which resulted in only seven trials for each duration, size and clutter combination, lower than recommended for accurate fitting of a psychometric function without significant bias[88,89]. Trials were filtered on the basis of reaction times; we set limits for trialwise reaction times to be above 100 ms and below 1 s. We chose this threshold, rather than a distributional one, to reflect the potentially wider range of reaction times resulting from collecting data online. For the GLMM analysis, model comparisons were carried out via chi-squared tests of model complexity. Fixed effects were measured using likelihood ratio tests.

Experiment 3: temporal categorization of memorability images

Procedure. All participants performed the temporal categorization task as described for Experiment 1, but with a different set of images.

Specifically, we drew a set of images from the LaMem dataset (http://memorability.csail.mit.edu/index.html). This dataset contains 58,740 images from a number of distinct sources, each with a corresponding memorability score, reflecting the probability that the image will be recalled later[32]. Twenty-eight images were randomly sampled from each of seven equally spaced memorability bins, or ranges of memorability scores (Δbin ≈ 0.10390; Bin 1, 1–0.89610; Bin 2, 0.89610–0.79220; Bin 3, 0.79220–0.68831; Bin 4, 0.68831–0.58441; Bin 5, 0.58441–0.48051; Bin 6, 0.48051–0.37662; Bin 7, 0.37662–0.27273). Within each bin, there was uniform spacing among the scores, ensuring an overall spread across the selected images. The memorability scores were taken from the second training step provided in the LaMem files. This resulted in 196 visual stimuli split among seven different ranges of memorabilities. Additionally, we included here seven possible durations, again log-spaced between 300 and 900 ms; this was done to allow for better characterization of the psychometric function for use with the fitting routines described below. The combination of seven different memorability ranges and seven possible durations created a total of 42 possible conditions across 196 trials. Every image was seen at all seven durations, resulting in a total of 1,372 trials, which were divided into seven blocks to allow the participants a break. Each block was about 6 minutes, making the full experiment ~45 minutes.

Analysis. For this experiment, we had a sufficient number of trials per condition (28 trials per duration in each memorability bin) for characterizing a psychometric function. By doing so, this allowed us to calculate measures of bias and precision individually for each participant. Psychometric functions for each memorability bin were fit using psignifit v.4.0 (ref. 90). All data were fit using a right-tailed Gumbel distribution to account for the log-spaced nature of the tested intervals, from which the BP and CV were calculated. The BP was determined as the 0.5 point on the curve for categorizing stimuli as long, whereas the CV was defined as half the difference between the 0.75 and 0.25 points on the function divided by the BP[91]. As an additional step, we removed any participant with a BP value that exceeded the tested intervals in the stimulus set (less than 300 or greater than 900 ms) or a CV greater than 0.5. Using this conservative threshold, 20 participants were removed from the analysis.

Experiment 4: temporal reproduction and recall of memorability images

Procedure. Experiment 4 took place on two separate but subsequent days. In the first part, the participants performed a duration reproduction task, in which they were shown an image and asked to press and hold a button for the same duration for which the image was shown[92]. The same 196 images from the Experiment 3 were used for this task. The images were each presented for one of seven possible durations linearly spaced from 500 to 1,000 ms such that each duration was represented four times in each bin. On a given trial, the participants were first shown a fixation cross for 500 ms, then shown the image for its specified duration and then asked to reproduce the duration by pressing and holding a response key to match the presented duration. While holding the button down, the participants were shown an unfilled white square of the same size as the images as an aid for reproducing the duration. All 196 image reproduction events shown to a participant represented one block, and each participant was asked to complete six blocks of duration trials, with breaks in between, to finish the first part of the study. Prior to completing six blocks of duration trials, the participants were asked to complete three practice trials, which were equivalent to a typical duration reproduction trial, but with a white unfilled square of the same size as the images. After each practice trial, the participants were shown the numerical duration that they reproduced, and the target duration. When they were finished with three practice trials, they were asked to complete the normal trials. Each block of 196 trials took about 10 minutes, resulting in a total experiment time of about 60 minutes.

The second part was conducted in the same room, using the same monitor and keyboard configuration as the first task. Here, the participants performed a surprise memory recall task, in which they were shown images and asked whether those images had been shown in the duration reproduction task. The participants were not informed that they would perform the memory recall task at the outset of the first session. All 196 images from the reproduction task were included in the memorability task, with an additional set of 196 images (foils) selected evenly from the seven memorability score bins in the same way as the first set. All 392 images were shuffled, and each image was flashed on screen for one second; the participants were then given a choice to press the 'y' key on the keyboard to indicate that they had been shown the image in the reproduction task, or the 'n' key to indicate that they had not.

Analysis. For the temporal reproduction task, the reproduced durations were filtered by removing all trials more than three standard deviations from the mean for each participant. To examine the link between memorability and reproduced duration, and because each participant was shown the same 196 images for each of the seven possible durations, we averaged the reproduced duration for each possible image. An LMM analysis was then run on these reproduced times, with the memorability score for each image as a fixed effect and participant as a random effect. In contrast, to examine the link between reproduced duration and memorability, we performed a GLMM analysis of the binary accuracy scores for each image with the memorability score for that image and the average reproduced duration as fixed effects and participant as a random effect. We also included the slope of the memorability effect by participant as a random effect, to account for inter-participant differences in memorability; model comparison demonstrated that the variable slope model significantly outperformed a model with only a random effect of participant ($\chi^2(1) = 8.866$, $P = 0.011$). An additional examination of the variance inflation factor (VIF), a measure of multicollinearity, revealed a VIF of 1.0006, below the commonly used threshold of VIF = 5 for indicating concerns[93].

As an additional analysis, we applied a Bayesian observer–actor model to the data from the temporal reproduction task[40,41]. This model, based on the work of Jazayeri and colleagues[38,39] and available at https://jazlab.org/resources/, conceives of performance on a time reproduction task as arising from an initial sensory measurement of the presented interval, modelled as a Gaussian distribution that scales with the size of the presented interval and that is integrated with a uniform prior distribution set to the range of presented intervals to form a posterior distribution of the interval estimate, which is then corrupted by production noise, also modelled as a Gaussian distribution. Model parameters for the measurement and production widths were fit using MATLAB v.2023a's (https://www.mathworks.com) fminsearch function for the reproduced durations for each of the seven memorability bins. Model fits were repeated ten times using a fitting maximum of 3,000 iterations; inspection of the fitted parameters indicated good convergence of the results.

Neural network modelling

To investigate the link between our memorability findings and computational models of vision, we implemented an artificial neural network modelling framework, in which a comparison between behaviour and network responses could be compared[94]. For the computational model, we employed an rCNN of the visual system. This model, termed 'BLnet', was designed to mimic recurrent processing within the ventral visual stream, in which individual layers project back onto themselves[50]. Critically, this framework entails 'unrolling' the model in time, such that with subsequent time steps in the model, layer-specific activity is fed back onto itself via lateral input. Thus, a single time step refers to a single 'sweep' of the model. We note that the length of the time step here is arbitrary; indeed, the model produces identical results whether the time steps are explicitly or implicitly encoded. Rather, the model relies on a difference in the stage at which layer-specific outputs are sent via bottom-up and lateral connections[49].

Our choice of BLnet in this case was motivated by the demonstration that rCNN models provide a better match to the sequential and time-varying nature of information flow across the ventral visual stream, as well as demonstrations that the BLnet architecture can reliably predict human reaction times and accuracy in response to visual stimuli[50,52]. CNNs by themselves have no access to temporal duration; by adding recurrent time steps, even arbitrary ones, rCNNs can provide outputs that vary as a function of time step. Here we used the BLnet code as provided at https://github.com/cjspoerer/rcnn-sat; the BLnet model was trained on object recognition using the ImageNet and Ecoset[95] databases across eight time steps. At the readout layer, the model provides classification output in the form of a softmax probability distribution. Crucially, this distribution is provided for each of the time steps in the BLnet model and therefore provides a window into how image classification is refined over time. More specifically, the softmax distribution converges on a set of image classifications over time, maximizing their probability while minimizing the probability of other categories. To quantify this, we calculated the Shannon entropy of the softmax distribution at each time step, as done in previous work. The resulting entropy by time response thus quantifies the degree of certainty in the classification over time. By setting a response threshold on these entropy values, we can predict human responses.

In the present study, we fed all 196 images from the memorability experiments into BLnet and calculated the resulting entropy of the eight time steps for each one. We then compared entropy values across the seven memorability bins to examine differences in model certainty by memorability. To compare with human performance, we used the model output to set an entropy threshold for classifying images into duration categories. Specifically, we set an arbitrary threshold and categorized all images as ‘long’ if the entropy value fell below that threshold and ‘short’ if it fell above it. This process was repeated at each of the eight time steps, after which the average proportion of ‘long’ responses was calculated for each time step. To match model performance to human responses, we repeated this process across a range of entropy scores spanning the largest to smallest entropy values in the dataset. For each threshold, as a first step, we calculated the average proportion of ‘long’ responses across all time steps for each of the seven memorability bins; a psychometric function was then fit to these data using the same method as described for the bisection data of Experiment 3, from which the BP was extracted. A linear regression of the BP values across memorability bins was then fit and the slope extracted; this step was designed to mimic the bias effect observed in behavioural data. Accordingly, a positive slope in the linear regression would indicate that the average proportion of ‘long’ responses decreased with higher memorability bins (recall that higher bins indicate lower memorability scores). As a second step, we calculated the slope of a linear regression of the CV values extracted from those same psychometric functions; this step was designed to mimic the precision effect observed in the behavioural data. Here, a positive slope would indicate that the CVs of the psychometric functions decrease with higher memorability bins. From these two values, we found the single entropy threshold with the lowest slope value for each effect.

As an additional measure to quantify the rate of decrease in entropy values (E) across time steps (T), we fit the data with a simple power curve model

$$E_T = A \times T^B + C$$

where the first parameter A determines the rate of decrease in entropy values and the parameters B and C reflect additional constants for the fitted curve, but were not analyzed here; more negative values indicate a faster rate of decline. These values were calculated for all 196 images in our sample, and the resulting values were compared across memorability bins via a repeated-measures analysis of variance.

Reporting summary

Further information on research design is available in the Nature Portfolio Reporting Summary linked to this article.

Data availability

All behavioural data for these experiments, as well as the rCNN results and memorability images used, are available at https://doi.org/10.17605/OSF.IO/FX3N2 (ref. 96).

Code availability

All relevant toolboxes and code repositories are cited in the text. The code is available at https://doi.org/10.17605/OSF.IO/FX3N2 (ref. 96).

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Author contributions

M.W., A.D.C. and A.C.M. conceived of and designed the experiments. A.D.C. and A.C.M. collected and analysed the data, with consultation and additional analyses by M.W. A.C.M. and M.W. wrote the manuscript.

Competing interests

The authors declare no competing interests.

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Data collection	All data were collected using Psychopy version 2020 and above. Experiments 1-3 were collected using the online platform Pavlovia due to the Covid-19 pandemic, whereas Experiment 4 was conducted in person after restrictions had been lifted.
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Reporting on sex and gender	Data were collected with no specific design towards sex and gender, which additionally were not experimental covariates.
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Population characteristics	Subjects were recruited from the undergraduate pool of students at GMU, ranging in age from 18-35 years old. All subjects were right-handed.
Recruitment	All subjects were recruited at GMU via an online system (SONA systems) for undergraduates to get credit for participating in research through Psychology courses.
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Research sample	Data were randomly collected from the GMU undergraduate pool via the SONA recruiting system, which provides course credit to Psychology students taking classes through the department. Sample sizes were chosen on the basis of previous studies. Gender makeup was (59% female, 25% male, 16% not declared). Experiment 1 included 52 subjects (mean age = 20.5, SD = 5.6), Experiment 2 included 50 subjects (mean age = 21, SD = 4.8), Experiment 3 included 48 subjects (mean age = 20.3, SD = 2.5), and Experiment 4 included 21 subjects (mean age = 21.2, SD = 3.66). The rationale for this sample is that it is representative of undergraduates at GMU and commonly tested in Psychology experiments.
Sampling strategy	Data were sampled randomly. All experimental conditions were within-subject, so there was no stratifying of our sample into separate groups. The sample size was determined on the basis of previous experiments by our lab and other groups studying time perception effects in humans.
Data collection	Experiments 1-3 were conducted using the Pavlovia platform, and so each subject performed the task on their personal computer or workstation. Experiment 4 was conducted in person using a PC with a 1000Hz gaming keyboard and a 120Hz gaming monitor. No one was present for Experiment 4 except the participant and the researcher, who was not blind to the research design and hypothesis.
Timing	Experiments 1-3 were conducted in Spring of 2021. Experiment 4 was conducted in Fall of 2022 and Spring of 2023.
Data exclusions	For Experiment 3, we excluded subjects with a bisection point outside the range of tested intervals, or a CV of above 0.5. This was done to ensure that the data in Experiment 3 were accurate; a total of 20 subjects were removed using these criteria. For

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