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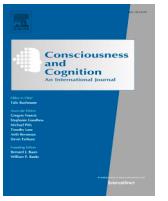

Distinctive features of experiential time: Duration, speed and event density

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ABSTRACT

William James's use of "time in passing" and "stream of thoughts" may be two sides of the same coin that emerge from the brain segmenting the continuous flow of information into discrete events. Herein, we investigated how the density of events affects two temporal experiences: the felt duration and speed of time. Using a temporal bisection task, participants classified seconds-long videos of naturalistic scenes as short or long (duration), or slow or fast (passage of time). Videos contained a varying number and type of events. We found that a large number of events lengthened subjective duration and accelerated the felt passage of time. Surprisingly, participants were also faster at estimating their felt passage of time compared to duration. The perception of duration scaled with duration and event density, whereas the felt passage of time scaled with the rate of change. Altogether, our results suggest that distinct mechanisms underlie these two experiential times.

1. Introduction

Psychological time is not monolithic and seldom follows physical time (Dennett & Kinsbourne, 1992; van Wassenhove, 2009). The subjective experience of time passing has been argued to be an illusion (Gruber & Block, 2013; Gruber et al., 2018; but see van Wassenhove, 2023), in that what we perceive as the 'flow of time' could better be understood as a 'flow of events' in time (Michon, 1972; Hicks et al., 1977; Fraisse, 1984; Gruber et al., 2018). In other words, psychology and cognitive sciences tend to attribute the term (psychological) 'time' to phenomena caused by the constant flux of changes, whether they are sensory events in the environment or fluctuations of bodily-clocked signals. Humans and animals can effectively keep track of how long events seem to last (duration perception), feel that time passes (passage of time) and assess the speed with which it seems to pass (Wearden, 2015).

Interestingly, whether estimating a duration and the felt speed of time result from the same timing mechanisms is unclear. At first glance, the length of a time interval and its felt speed seem to be clearly related: short durations are perceived as passing quickly while long durations are experienced as passing slowly (Martinelli & Droit-Volet, 2022b, Nicolaï et al., 2023). However, this relation does not always hold and is likely to be more nuanced. For instance, individuals who suffer from depression report a significantly slower passage of time, despite their estimation of duration being comparable to that of healthy individuals (Thönes & Oberfeld, 2015). This observation, along with previous research, suggests that temporal judgments (felt speed and duration) may capture distinct

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psychological phenomena (Droit-Volet & Wearden, 2015; Droit-Volet et al., 2017; Jording et al., 2022).

Passage of time judgments have been hypothesized to capture the most salient (external or internal) contextual changes experienced in a given time interval (Martinelli & Droit-Volet, 2022b). This proposal is compatible with the contextual change hypothesis (Block & Reed, 1978), in which perceiving the duration of an event results from the number of changes in a context, whether duration is estimated prospectively or retrospectively (Block & Reed, 1978; Zakay & Block, 1997). Although both proposals suggest that contextual changes are the source of temporal experience, they appeal either to duration or to speed. If long durations are linked to slow speed (Martinelli & Droit-Volet, 2022b), one would expect that longer durations would be linked to a slower experience of time passing. However, this contradicts the observation that while fewer events do shorten perceived duration (Jording et al., 2022; Roseboom et al., 2019), fewer events also slow down the experienced speed of time (Jording et al., 2022), raising questions about the underlying mechanisms giving rise to these temporal phenomenologies and their interplay.

Given that our environment is in a constant state of change, it is unsurprising that perceptual changes would relate to our experience of time. Beyond transient perceptual changes, our brain keeps track of ongoing experiences by segmenting the continuous flow of information into meaningful units or distinct mental "events" (Zacks & Tversky, 2001). Models of event segmentation suggest that the passage of time may be a side effect of constructing and updating event representations (Richmond & Zacks, 2017). In such models, events are functionally defined within a clear temporal framework (Zacks & Tversky, 2001). Contextual changes, perceptual or abstract, affect duration judgments as predicted by the contextual change hypothesis (Hicks et al., 1976; Block & Reed, 1978): the more events, the longer durations are estimated or remembered to be (Brunec et al., 2020; Ezzyat & Davachi, 2014; Roseboom et al., 2019). With respect to speed, a recent study showed that a perceived higher rate of changes in an optical flow display also sped up felt time (Jording et al., 2022). Hence, both duration and speed are influenced by perceptual changes, but whether contextual changes systematically affect them in a similar way is unknown.

In the present study, we investigated how event segmentation influences experiential duration and speed of time. We chose to test realistic contextual changes and events as defined by event segmentation theories in contrast to salient perceptual changes. Stimuli were videos of a train station lasting 17 s to 23 s, with a varying number of distinguishable events that would naturally occur in such an ecological context. One novel goal was to validate duration and speed measurements for long time scales in the range of seconds. We opted for a bisection task, commonly used for short duration estimations. Bisection tasks (Kopec & Brody, 2010) are 2-AFC (Alternative Forced Choice) tasks in which participants must select one of two possible options when presented with a stimulus. Herein, participants were provided with a 2-AFC using short or long for the Duration task and slow or fast for the Speed task. Each stimulus was drawn from a parametrically varied continuum of durations. This psychophysical approach allowed fitting a psychometric curve and deriving the subjective threshold (point of subjective equality [PSE]) and just-noticeable-difference (JND). Reaction times (RTs) were also recorded as participants were instructed to perform as accurately and as fast as possible. This approach allowed going beyond the typical Likert or visual-analog-scale used for passage of time ratings (Wearden, 2015).

Since shorter durations yield faster experienced speed (Martinelli & Droit-Volet, 2022b; Nicolaï et al., 2023), we expected that estimations of the speed of the passage of time would scale with video duration, allowing the use of a psychometric approach. Additionally, we anticipated scenes with fewer events to result in a slower experience of time passing but in longer duration estimates. Finally, we hypothesized that the presence of a different type of contextual event (in our case, a train) would influence both temporal measurements due to its salience as the most expected event in the context of waiting at a train station, whereas its absence is surprising. Hence, in agreement with event segmentation theories, we predicted that the absence of a train would lead to an overestimation of duration and a deceleration of felt time.

2. Materials and methods

2.1. Participants

166 adult participants, aged 18 to 51 y.o. (mean = 27.98 y.o., SD = 7.81; 121 females) were recruited in the online study. Participants reported no history of neurological or psychiatric disorders. 143 participants self-declared as right-handed and 23 as left-handed. Participants were recruited online through academic mailing lists and social media. All participants gave their written informed consent for participating before the beginning of the experiment. All participants were compensated for their participation (15€ per hour). The study was approved by the Comité d'Ethique pour la Recherche of Paris-Saclay University (CER-Paris-Saclay-2019-063) and ran in accordance with the declaration of Helsinki (2013). Two participants failed the training and did not advance to the main task. One participant was a priori excluded from all psychometric analyses due to poor performance reflected in extreme deviance values and flat curves. Thus, a total of 163 participants were included in the analysis (mean = 27.97 y.o., SD = 7.85; 118 females).

Participants could take part in either one or both tasks (Duration and/or felt Speed). Out of the 163 participants, 52 were tested on the Duration task only, 50 were tested on the Speed task only and 62 contributed to both tasks. This allowed for two kinds of analytical approaches: a between-participants assessment ($N_{Duration} = 85$; $N_{Speed} = 78$) and a within-participants analysis ($N = 62$).

2.2. Stimuli

Stimuli were realistic videos of a virtual train station created using the Unity software (Haas, 2014). A total of 40 videos (mp4) were created to manipulate the factors of stimulus duration (5), number of events (Events: 2) and train (Train: 2). Stimulus duration refers to the total duration of the video, which could be 17 s, 19 s, 20 s, 21 s or 23 s (i.e., 20 s +/- 5 % or +/- 10 %). The number of events in each

video could be three or seven. To best simulate the ecological experience of waiting on the dock of a train station, the events added to the environment were the kind expected in such context, and consisted of either human activities (e.g. a person walking while texting) or the passage of a train (refer to Table S1 in Supplementary Material for full list). In half of the videos, only human activities were used and no train event occurred (20 videos); in the other half, one of the events was a train passing by, arriving at or leaving the station allowing for a balanced design of two distinct blocks of videos depending on our third factor, the train. Subtle background sounds of a train station were added to each video and the train event was accompanied with the corresponding sound effect.

2.3. Task design

The experiment was coded in JavaScript using the jsPsych library (De Leeuw, 2015). The experiment was hosted on a dedicated server for online experiments at Neurospin (CEA, France). It consisted of two 1-IFC 2-AFC bisection tasks, which tested duration estimation and felt speed. The factor Train followed a block-design: the two blocks (Train, No Train) were randomized across participants. Each stimulus duration was presented 4 times in each block. The durations of the video and the number of events were randomized within blocks.

When a participant logged onto the server, the order of the tasks was randomized so that the experiment could start with the Duration or with the Speed bisection task. At the end of the first task, participants could continue to the second task or end their participation in the study. In a given task, participants were presented with one video at a time, which they classified into one of two categories: “Short” or “Long” for the Duration bisection and “Fast” or “Slow” for the Speed bisection (Fig. 1).

The motor-response mapping was congruent with the Spatial-Numerical and the Spatial-Temporal Association Response Code (SNARC and STARC, respectively) (Fabbri et al., 2012). According to the SNARC and STARC effects, participants’ responses are facilitated by the ranking of the responses (small numbers or durations on the left, large numbers or durations on the right in the SNARC and STARC, respectively) (Hubbard et al., 2005; Ishihara et al., 2008). The Simon effect, according to which responses are facilitated when the position of the response key is congruent with its appearance on the screen, was also taken into account (Hommel, 2011). Hence, in the Duration bisection task, participants were asked to respond with the left arrow key for “Short” presented on the left of their screen and with the right arrow key for “Long” presented on the right of their screen. Keys in Speed bisection followed the same pattern (left for “Fast” and right for “Slow” responses) for consistency.

Both accuracy and speed of responses were emphasized in the instructions. Participants’ responses and reaction times (RTs) were recorded on each trial. RTs were capped to 4 s and skipped trials were rethrown at the end of the block. If an answer was not provided within the available time, a warning message appeared prompting participants to respond faster.

2.4. Procedure

Before the beginning of the main task, all participants were trained by being presented with the longest and the shortest duration videos. For speed, they were presented with the longest with 3 events and the shortest with 7 events for “slow” and “fast” choices. During the training, participants were provided with feedback. An incorrect response resulted in the rethrow of the training phase (up to three times). Only participants who correctly distinguished the two extreme stimuli could take part in the study.

At the end of the experiment, participants rated three separate emotional states (happiness, sadness and boredom) on a Likert scale

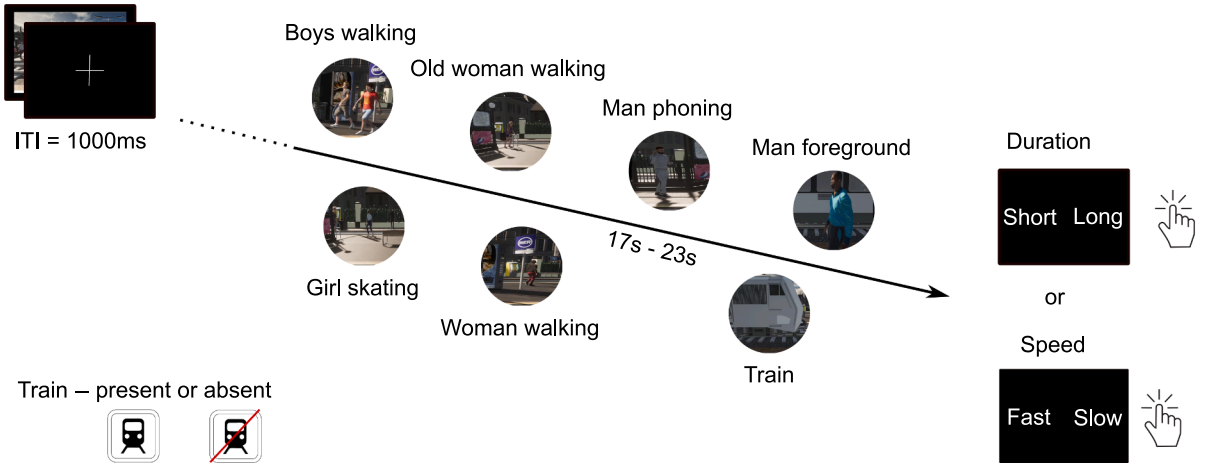

Fig. 1. Task Design. Videos of a virtual Parisian regional train dock were used as stimuli. Videos could contain 3 or 7 events, one of which could be a train. The experiment was a 5 (durations: 17 s, 19 s, 20 s, 21 s, 23 s) x 2 (train or no train) x 2 (3 or 7 events) design. Participants were asked to categorize each video as ‘long’ or ‘short’ in the Duration bisection task, or as ‘slow’ or ‘fast’ in the Speed bisection task. The factor Train was tested in a block design randomized within participants: one experimental block tested 20 videos without a train, another one tested 20 videos with a train. The order of the Tasks was randomized across participants.

ranging from 1 ("not at all") to 4 ("very much"). Participants also rated and provided their comments on the difficulty of the task and on the strategy they used (if any) to classify the stimuli.). These responses can be found in Fig. S1 and table S2 in the Supplementary Material.

2.5. Psychophysical quantification

Psychometric curves were generated for each individual using the proportion of 'slow' responses for Speed and 'long' responses for Duration. Four (Duration *or* Speed) or eight (Duration *and* Speed) psychometric curves were fitted by participants for each number of events (3, 7) and Train (present, absent) combination. The mean RT for each combination of duration, number of events and train was computed per participant and a log transformation was performed for further analyses.

Fits were done using the psignifit python version 4.0 (Schütt et al., 2016). The Duration and Speed data were fitted using a cumulative Gumbel distribution. The less steep right side of the Gumbel sigmoid function best reflects the scalar properties of timing that is to say, the fact that variability in temporal discrimination increases with mean subjective time i.e, longer durations are associated with greater variance (Allan, 1998; Van Driel et al., 2014; Wiener et al., 2018).

To assess each individual's goodness of fit, the Deviance was used: Deviance was defined as two times the difference of the model log-likelihood to the log-likelihood of the best fitting model (Schütt et al., 2016; Wichmann & Hill, 2001). A critical Deviance value was calculated by generating 2000 datasets using the best-fitted function and obtaining the 95 % confidence interval of the resulting deviance distribution. A Deviance of the data superior to the criterion indicated a bad fit. Bad fits were excluded from the analysis and accounted for less than 5 % and 6 % of the total dataset for the Duration and Speed, respectively. Individual examples of good and bad fits are provided in Fig. S2-A and B. The Deviance distributions for all psychometric fits are provided in Fig. S2C. From the psychometric fits, we calculated the Point of Subjective Equality (PSE) and the Just Noticeable Differences (JND). The PSE (50 % threshold) is an indication of bias towards one of the two possible responses while the JND (the functions interquartile range) reflects the participant's precision (Vatakis et al., 2018).

To directly compare the effect of the number of events in duration and speed, we calculated the difference in the PSEs between the two event conditions (7 – 3) for all participants, who performed both tasks (henceforth referred to as ΔPSE). Seven participants with bad fits were excluded. The ΔPSE reflects the bias following the change in the number of events. A negative ΔPSE indicates that

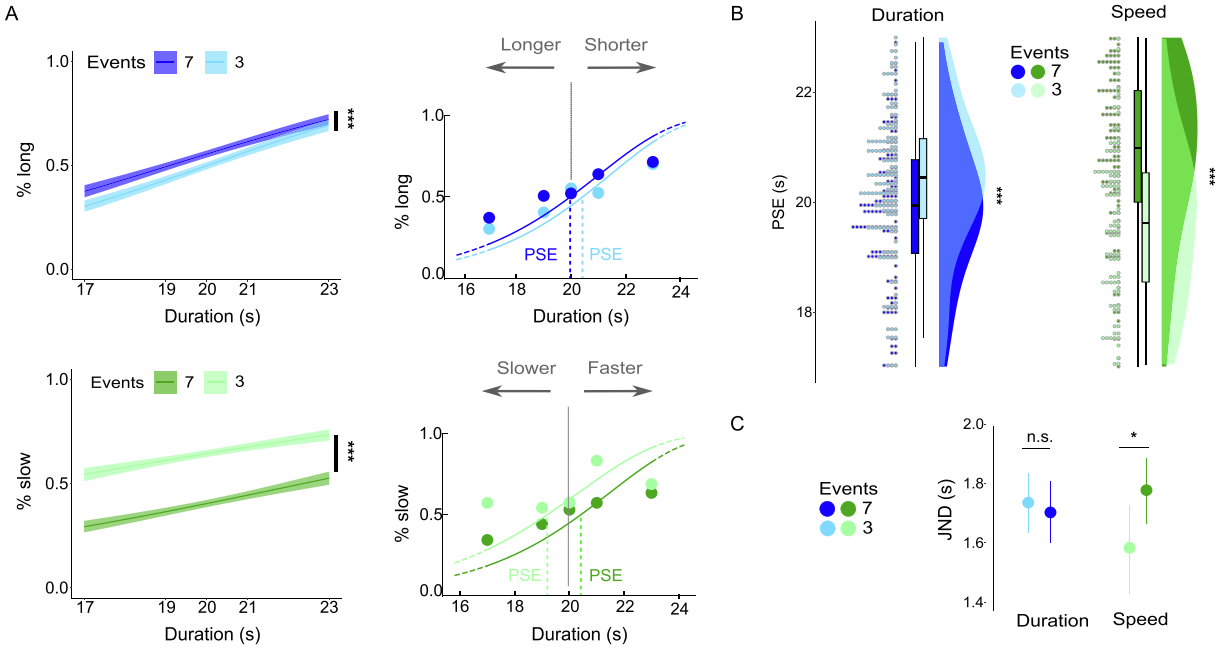

Fig. 2. The number of events influences both experiential duration and speed of time. A. Left: percentage of 'long' and 'slow' responses (Duration, blues in upper panels and Speed, greens in lower panels, respectively) as a function of stimulus duration for 3 (light) and 7 (dark) events. Longer videos significantly increased the odds of responding 'long' and 'slow' in Duration and Speed, respectively. The number of events increased the odds of responding 'long' in Duration and decreased the odds of responding 'slow' in Speed. Right: percentage of 'long' (left) and 'slow' (right) responses as a function of video duration for 3 (light) and 7 (dark) events. Dots are mean responses across participants (N = 85 for Duration; N = 79 for Speed). Mean psychometric curves are for illustration purposes. A leftward shift of the curve (lower PSE) indicates a bias towards 'long' or 'slow' responses, respectively. A rightward shift (higher PSE) indicates a bias towards 'short' or 'fast' responses, respectively. B. Distribution of individual PSEs as a function of duration and number of events (light and dark colors for 3 and 7, respectively) in Duration (left, blues) and Speed (right, greens). Dots are individuals. C. Mean JND as a function of the number of events. Error bars are the 95 % CI. Significance codes: $p < 0.001$ '***'; $p < 0.01$ '**'; $p < 0.05$ '*'; $p > 0.05$ 'ns'.

increasing the concentration of events biases towards 'long' or 'slow' responses; conversely, a positive ΔPSE indicates a bias towards 'short' or 'fast' responses.

2.6. Outliers

Conditions in which the PSE fell outside the range of tested durations were excluded in all statistical analyses. In Duration, ~10 % (32 out of 340 conditions) of the PSE fell outside the range of tested durations. In Speed, ~28 % (90 out of 316 conditions) of PSE fell outside of the tested range (examples are provided in Fig. S1D). In the within-participants analysis, 11 % of conditions were excluded in Duration (29 out of 252) and 22 % in Speed (55 out of 252).

2.7. Statistical analyses

All analyses were conducted using the R software (R Core Team, 2022) with Rstudio (RStudio Team, 2020). For RTs and psychometric parameters analysis, we used linear mixed models with a random intercept for participants. Models were fitted using the lme4 package for R (Bates et al., 2015) and p-values and degrees of freedom were obtained with the lmerTest (Kuznetsova et al., 2017) and car (Fox & Weisberg, 2019) packages. The emmeans package (Lenth, 2022) was used for pairwise comparisons for PSE.

The goodness of fit of the models and the significance of fixed effects was assessed using the Akaike Information Criterion (AIC) and Wald $\chi 2$ tests. For the JND analysis, the conditions for a parametric statistical approach were not met and so aligned rank transformation (ART) was performed on the data using the ARTool (Kay et al., 2021) followed by a repeated measures three-ways Anova.

For the analysis of the raw data to assess the feasibility of a psychometric curve, a mixed effect logistic regression model was used with duration and number of events as variables.

All statistical tests were performed against an alpha level of $p < 0.05$. All plots were generated with the ggplot2 package for R (Wickham, 2016).

3. Results

3.1. The experienced duration and speed of passage of time scale with duration

Before psychometric modeling of the data collected in each task, we first established whether responses in both tasks scaled with the duration of the video. For this, we used a mixed effect logistic regression model to analyze the effect of the duration and number of events on the probability of 'long' and 'slow' responses for the Duration and Speed bisection tasks, respectively. This approach was realized using all data with no prior assumption on their psychometric profiles (Fig. 2A) since no fits were realized to perform this analysis (cf. Fig. S1). Longer durations increased the probability of 'long' responses in Duration (OR = 1.17, 95 % C.I. [1.14, 1.2], $p < 0.001$; Fig. 2A top) and of 'slow' responses in Speed (OR = 1.3, 95 % C.I. [1.27, 1.33], $p < 0.001$; Fig. 2A bottom). The number of events significantly affected duration and speed estimates: in Duration, the odds of responding 'long' were higher when videos contained 7 events than when they contained 3 events (OR = 0.79, 95 % CI [0.71, 0.87], $p < 0.001$). Conversely, the odds of responding 'slow' in Speed were higher with fewer events (OR = 2.77, 96 % CI [2.49, 3.08], $p < 0.001$). Thus, a first experimental observation is that for a given time interval, a larger number of events lengthens subjective duration, and accelerates participants' felt passage of time as compared to a smaller number of events.

In both Duration and Speed, a scaling of responses as a function of elapsed time was found. We thus proceeded with individual psychometric fits to extract individuals' PSE and the JND. Fig. 2A–B, right panels, illustrate the mean responses across participants for Duration and Speed, respectively.

3.2. More events lengthen duration and increase the speed of the passage of time

As in the previous analysis, we found that the number of events in the videos significantly affected time estimation in both Duration and Speed bisection tasks. In Duration (Fig. 2B, blues), consistent with the results of Fig. 2A, the PSEs were significantly higher in the 3-events videos as compared to the 7-event ones (0.53, 95 % CI [0.25, 0.82], $t(219.5) = 3.69$, $p < 0.001$) signifying that participants underestimated the duration of the videos when the number of events was small. We found no significant effects of the number of events on JND ($F(1, 216.5) = 0.006$, $p = 0.94$; Fig. 2C, left panel) or on RTs ($\chi 2(1) = 0.78$, $p = 0.38$) (Fig. S3A and Table S3 in Supplementary Material). In Duration, the number of events biased participants' responses without affecting their sensitivity.

In Speed, the number of events significantly affected RTs, PSE and JND. A significant decrease in PSE was found for videos containing 3 events compared to 7 events (−2.41, 96 % CI [−3.12, −1.7], $t(161.35) = -6.59$, $p < 0.001$; Fig. 2B). This indicates that participants favored a 'slow' response in videos containing fewer events. The number of events also significantly affected the JND so that 3-event videos yielded a significantly smaller JND than the 7-event videos ($F(1, 157) = 31.22$, $p < 0.001$; Fig. 2C, right panel). RTs in Speed were also significantly slower for 3-event videos as compared to the 7-event ones (0.44, 95 % CI [0.17, 0.7], $t(1498) = 3.22$, $p < 0.01$; Fig. S3B and Table S4 in Supplementary Material). Thus, for a given duration, when a video contained a smaller number of events, participants were slower (RTs), tended to experience time as passing slower (PSE), and were more sensitive to the speed of the passage of time (JND).

3.3. When trains alter the experience of time

In Duration, the presence of a train did not significantly affect the PSE ($\chi 2(1) = 2.38$, $p = 0.12$) but significantly influenced the JND ($F(1, 216.5) = 12.9$, $p < 0.001$) (Fig. 3A). Participants showed greater sensitivity to changes in duration when there was no train in the video (Fig. 3A, bottom). We found a significant effect of Train on RTs (0.03, 95 % CI [0.01, 0.06], $t(1613) = 2.78$, $p < 0.01$; Fig. S3A and Table S3 in Supplementary Material) with faster RTs when a train was present in the video. Additionally, we checked if the order of the Train blocks influenced the psychometric parameters. The block order significantly affected the PSE (−0.62, 95 % CI [−0.94, −0.32], $t(74.72) = -3.94$, $p < 0.001$) so that the PSE was smaller when the train was presented in the first block as compared to when it was presented in the second block (Fig. S4A and Table S5 in Supplementary Material for the full model). Hence, participants were biased towards overestimating the duration of the first block when it contained a train event.

In Speed, the presence or absence of a train significantly affected the PSE (−2.41, 95 % CI [−3.12, −1.69], $t(148.97) = -3.09p <$ 0.001; Fig. 3B, top) so that the presence of a train sped up felt time. Additionally, we found a two-way interaction between Train and number of events (0.99, 95 % CI [0.25, 1.73], $t(157.97) = 2.6$, $p = 0.01$) and Train and block order (1.12, 95 % CI [0.38, 1.85], $t(158.1) = 2.94$, $p = 0.01$). These interactions show that the number of events affected the PSE less when one of the events was a 'train' (Fig. 3B) and when the first block contained a train event (Fig. S4B and Table S6 in Supplementary Material for the full model). The

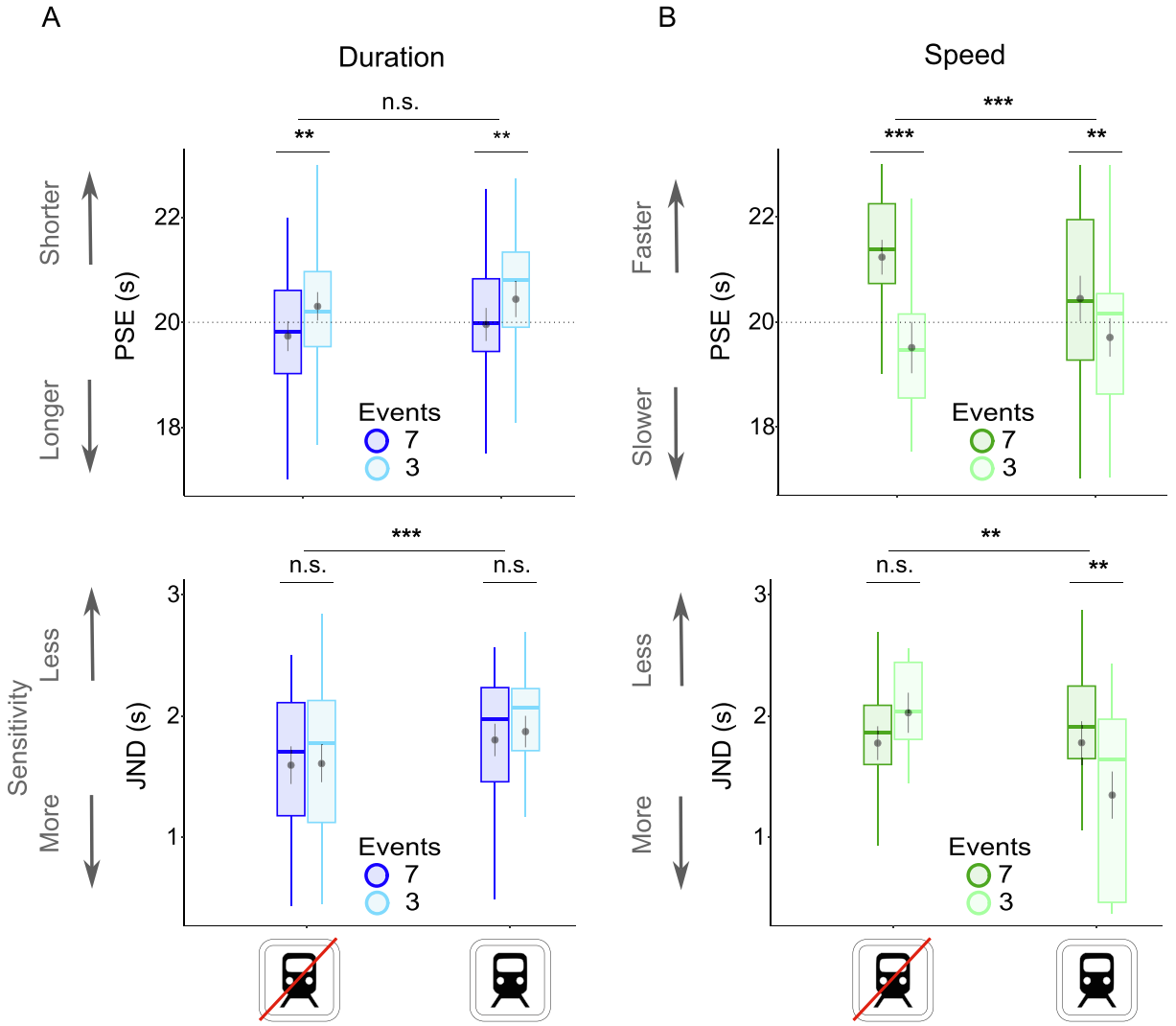

Fig. 3. The presence of a train influences duration and speed estimates. A. PSEs and JNDs in the Duration bisection task. Boxplots indicating the mean and 95 % C.I. of PSE (top) and JND (bottom) extracted from individual psychometric fits in the train (left) and no train (right) blocks for the 3- and 7- event videos (light and dark blue, respectively). B. PSEs and JNDs in the Speed bisection task. Boxplots indicating the mean and 95 % C.I. of PSE (top) and JND (bottom) from individual psychometric fits in the train (left) and no train (right) blocks for 3- and 7- event videos (light and dark, respectively). Mean estimates and 95 % C.I. are provided. Significance codes: $p < 0.001$ '***'; $p < 0.01$ '**'; $p < 0.05$ '*'; $p > 0.05$; 'ns'. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

presence of the train also significantly affected the JND ($F(1, 150.31) = 8.67$, $p < 0.01$) with lower JNDs observed when a train event was present in the video (Fig. 3B, bottom). We also found a significant interaction between the number of events and the Train ($F(1, 158.49) = 16.35$, $p < 0.001$; Fig. 3B) on the JND. Last, the factor Train did not influence RTs ($\chi2(1) = 1.93$, $p = 0.16$; Fig. S3C and Table S4 in Supplementary Material). Altogether, these results indicate a major effect of the presence of a train in the estimation of the speed of felt time, highlighting the importance of contextual effects in experiential time.

3.4. Relation between duration and speed judgments

To characterize more precisely the relation between duration and speed of time, we analyzed data collected within-participants ($N = 62$). In the within-participant design, the effect of the number of events on PSE was significant in both tasks (Duration: 0.69, 95 % CI [0.27, 1.08], $t(197) = 3.43$, $p < 0.001$; Speed: −0.93, 95 % CI [−1.35, −0.5], $t(126.27) = -4.3$, $p < 0.001$; Fig. 4A). Consistent with our previous analyses, participants favored short durations but slow speed for stimuli with a low number of events as illustrated by an increase and decrease in the PSEs, respectively (Fig. 4A).

We then compared the data from the two bisection tasks directly keeping in mind that the speed of the passage of time may be computed as the number of events in a given time interval. This working hypothesis simply indicates that the duration and speed are

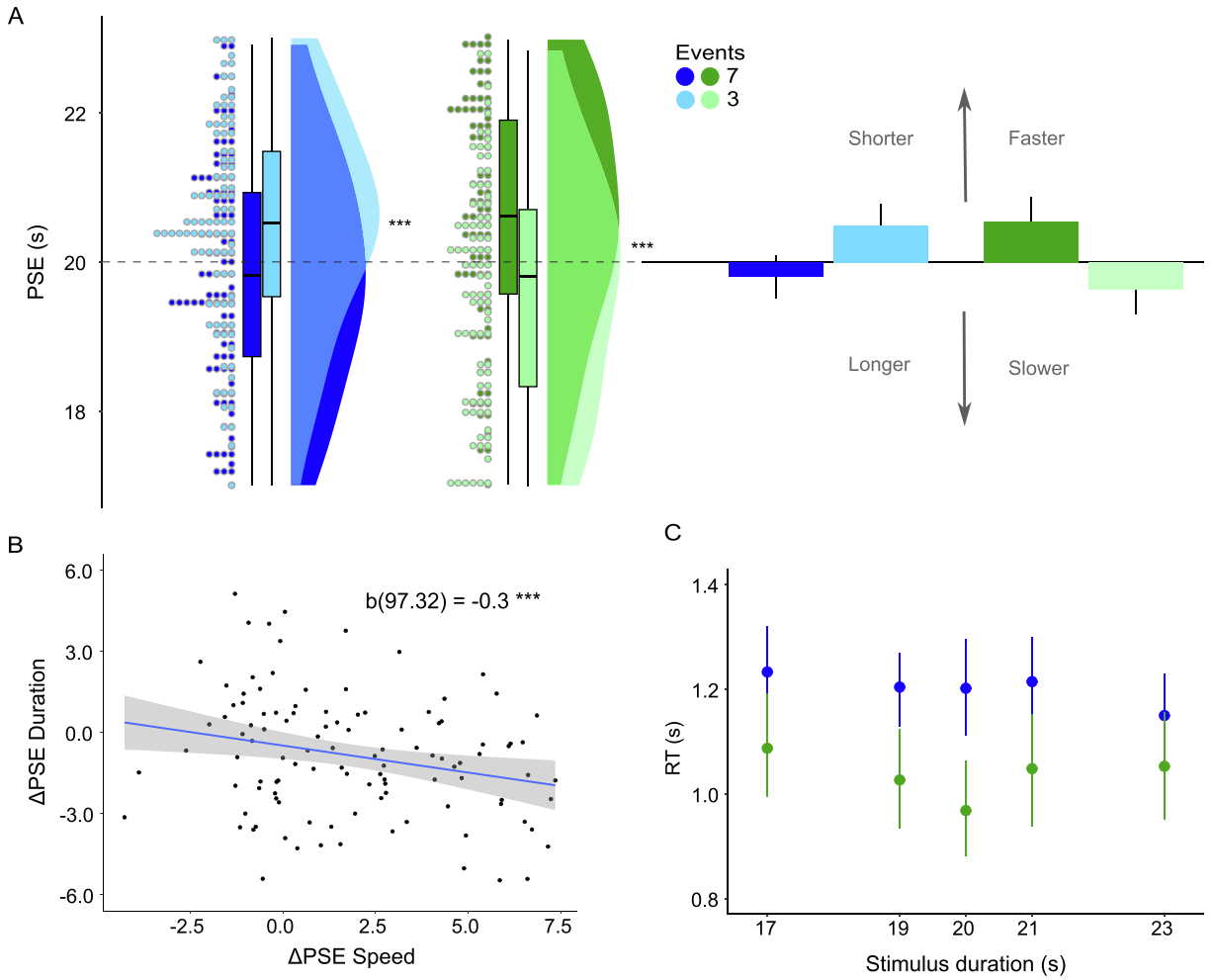

Fig. 4. Speed of the passage of time is dissociable from duration estimates (within-participant design). A. Left: Distribution of individual PSEs for Duration (left, blues) and Speed (right, greens) as a function of the number of events (light for 3 events; dark for 7 events). Dots are individuals. Right: Direction of biases: barplots provide the mean PSE and 95 % C.I. for Duration and Speed (blue and green, respectively). The black horizontal line shows the midpoint of the duration distribution used (i.e., 20 s). B. ΔPSE was computed as the shift of the PSE in the psychometric curve from 7 to 3 events in the Duration and in the Speed tasks, separately. ΔPSE in Duration as a function of ΔPSE in Speed shows a significant negative relation indicating that, given the same time interval, an increase in the number of events lengthens duration and speeds up the felt passage of time. Beta coefficient and degrees of freedom are shown. C. Mean RTs for each stimulus duration in both tasks. RTs in Speed bisection (green) were significantly faster than in the Duration bisection (blue). Error bars indicate 95 % C.I. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

inversely proportional to each other. First, we investigated whether the impact of the number of events on both temporal experiences was comparable. For this, we computed changes in PSE as a function of the number of events ($\Delta PSE = PSE_7 - PSE_3$) separately for both tasks. Using a linear mixed effects model, we evaluated the relation between ΔPSE in Duration and in Speed and found a statistically significant, albeit small, negative relation between the two (−0.3, 96 % CI [−0.48, -0.12], t(97.32) = −3.3, p = 0.001; Fig. 4B).

Second, given the working hypothesis, we predicted that speed would be computed after a duration had been represented so that the felt passage of time would be a direct outcome of event count in a given time interval. Therefore, we expected participants to be faster at estimating durations than at estimating the speeds of the passage of time. Participants' RTs significantly differed across tasks (−0.83, 95 % CI [−1.24, −0.41], t(586.58) = −3.93, p < 0.001) but participants were surprisingly much faster in answering the Speed task than the Duration task (Fig. 4C). This suggests that conscious access to estimates of the speed of felt time may be easier and faster than those of durations.

Last, we investigated whether event density (i.e., the number of events in a given duration) was a major driving factor in speed judgments. For this, we calculated the mean percentage of 'long' responses for Duration and the mean percentage of 'slow' responses for Speed as a function of event density. As we did not initially test for the density of events in our experimental design, the data points were not equally spaced, preventing the use of a balanced statistical analysis. Nevertheless, we observed that for Duration, the primary criterion for judgment remained the objective duration of the stimuli so that the density of events rescaled the judgments (Fig. 5A). However, in Speed, participants' answers scaled almost continuously with density irrespective of the tested duration (Fig. 5B).

4. Discussion

Our study explored how contextual changes using real-life events influence experiential duration and speed of time. First, we successfully used bisection tasks to assess seconds-scale duration estimation. Second, we extended this approach to assess the speed of the passage of time judgments, typically assessed using Likert or visual-analog scales. Psychometric assessments provide useful estimates of biases (PSE) and sensitivity (JND) of participants' experiential time. Third, we show that an increasing number of events in a scene lengthens its perceived duration (bias), accelerates felt time and decreases sensitivity to speed. Fourth, the absence of an expected event in a given context (here, a train) lengthens perceived duration, slows down felt time and decreases the sensitivity to experiential speed of time. We discuss below the link between the experience of duration and speed of time, and comment on the observation that speed scales with event density whereas duration increases with the number of events at a given scale.

Herein, we demonstrated the feasibility of a psychometric approach to characterize participants' felt speed of time classification as a function of the duration of videos. The assessment of PSEs indicated that shorter (longer) durations elicited faster (slower) experiential speed. This outcome indicates that speed can be modulated by the duration of external events, even when stimuli are videos of complex realistic scenes captured in a virtual environment. Our observation is consistent with previous research (Jording et al., 2022; Martinelli & Droit-Volet, 2022a, 2022b) in that experiential speed seems to scale with objective duration. Importantly, we report that increasing the number of events significantly accelerated participants' experience of the passage of time, in agreement with a recent visual starfield study assessing perceptual changes (Jording et al., 2022). Interestingly, we found that an increasing number of events decreased participants' sensitivity to speed, suggesting a potential trade-off between speed and the hierarchical level of event boundaries (Zacks et al., 2001; Zacks & Tversky, 2001). Our results converge with perceptual studies, in which sensory changes contribute to duration estimation (Roseboom et al., 2019; Ahrens & Sahani, 2011). However, we deliberately shifted our focus from perceptual changes to event segmentation, so that the granularity of change is an event in a realistic scene. Events exhibit complex characteristics, often involving animate agents engaged in goal-directed actions (e.g. 'woman walking', Fig. 1). Events are situations

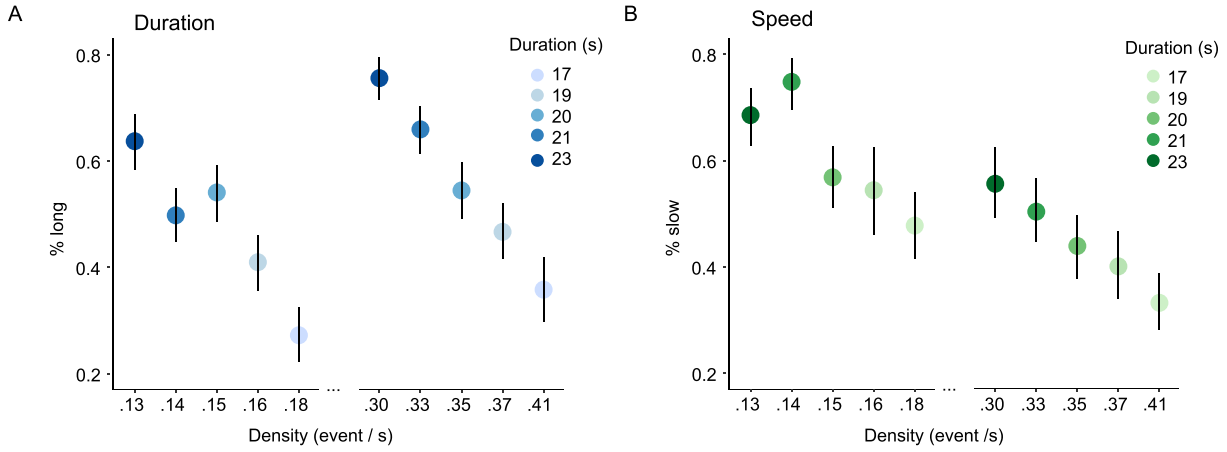

Fig. 5. Dissociable effect of event density on Duration and Speed. A. Mean % of 'long' responses for Duration for each video duration as a function of event density. Event density is defined as the ratio between the number of events and the tested duration. B. Mean % of 'slow' responses for Speed for each video duration as a function of event density. Speed of the passage of time judgments linearly scale with event density, whereas duration scales with number.

with specific spatiotemporal boundaries, formed spontaneously and continuously (Richmond & Zacks, 2017) and they include multiple salient or non-salient perceptual changes (Zacks et al., 2007). From this perspective, in agreement with the event segmentation literature (Ezzyat & Davachi, 2014; Brunec et al., 2020), we found that an increased number of events lengthens and accelerates experiential duration and speed of time, respectively. It is noteworthy that this runs counter-intuitive to the idea that longer duration implies slower times, suggesting that duration and speed reflect distinct psychological phenomena (Brighouse & Levitan, 2014; Droit-Volet & Wearden, 2015; Droit-Volet et al., 2017).

By analogy to canonical speed (i.e. traveled distance by unit of time), the phenomenology of the speed of time could reflect the rate of events per unit of time. One would expect that a time interval (e.g. 20 s) and the number of events in that interval (e.g. 7) need to be estimated before evaluating how fast the passage of time may feel (i.e., 7/20 resulting in 0.3 events/second). If this were the case, a first prediction would be that RTs in Duration should be faster compared to Speed. Counter to this prediction, our findings reveal instead that participants' responses were much faster in Speed than in Duration (by as much as ~100 ms). A second prediction would be that the effect of the number of events on Duration would be negatively correlated to the one on Speed. A weak correlation was indeed found. Our findings suggest that representing duration may not be a prerequisite for making a speed assessment and to the contrary, that a speed estimate may be computed earlier than a duration estimate. A consequence of this observation is that units of time must be available endogenously, before the full video has ended. This observation naturally lends itself to the notion of temporal structures (i.e. temporal windows or frames) within which information is integrated at distinct time scales (VanRullen & Koch, 2003; Gallagher & Varela, 2003; Pöppel, 1997, 2009; Wittmann, 2013). This observation is also compatible with recent neurophysiological proposals of time encoding (Issa et al., 2020; Tsao et al., 2022), the known existence of temporal windows of integration in perception (e.g. Yabe et al., 1998; Poeppel, 2003; van Wassenhove et al., 2007; Wutz et al., 2016) and in cortical hierarchies (e.g. Hasson et al., 2008; Lerner et al., 2011; Baldassano et al., 2017).

One explanation of our results is that faster passages of time may result from an increase in sensory information (i.e., noise) over time (Martin et al., 2017; Matthews & Meck, 2016). The speed of time would be influenced by the overall complexity of a scene, rather than relying on accurate estimates of duration. This explanation aligns well with the observed linear relationship between speed and event density across time scales. In an event segmentation framework, the constant updating of event models creates boundaries between the current representation and the previously held one (Richmond & Zacks, 2017; Shin & DuBrow, 2021). Therefore, the more boundaries are formed over time, the faster the experiential passage of time is predicted to be. This is also consistent with the decreased sensitivity to speed observed as the number of events increased. Importantly, duration estimates do not follow this trend. Instead, we observe a rescaling effect and a remarkable dependency on the objective video duration. No linear dependency with event density was found, and the number of events shifted participants' biases as expected (Ezzyat & Davachi, 2014).

The effect of temporal rate (or frequency) on duration has been largely explored in perception. Temporal rate can refer either to a single stimulus moving (e.g. grating) or flickering at a given temporal frequency, or to a series of simple stimuli that are perceived sequentially at a certain rate. The temporal frequency of a given stimulus has been shown to increase the duration of visual stimuli (Herbst et al., 2013) and rate adaptation yield subsequent stimuli to be compressed (Johnston et al., 2006; Eagleman, 2008; Matthews et al., 2014). Comparable distortions emerge when manipulating the predictability of a sequence (Tse et al., 2004; van Wassenhove et al., 2008). However, the simple stimuli used in these studies do not match the more complex dynamics of realistic scenes. Rather, the concept of rate of change goes beyond mere perceptual changes and encompasses dynamic changes in a scene that are parsed into higher cognitive constituents (e.g. a man is walking). Changes are not necessarily confined to a particular sensory modality and they extend beyond strictly perceptual aspects, thereby implicating mnemonic mechanisms and including internal mental states. Nevertheless, there exists a potential interplay between the temporal rate of stimuli in the environment and the rate of change in a scene, or even its segmentation into distinct episodes, that merits investigation (Howard & Kahana, 2002). This interaction holds promise for a more nuanced understanding of how temporal dynamics in a changing context relate to broader cognitive processes in scene segmentation.

Last, the presentation of a train event influenced both duration and speed. The mere presence of a train did not affect duration estimates, but the block in which the train appeared in the experiment did. Participants starting with a 'train' block tended to overestimate durations compared to those who started with a 'no train' block. One possible explanation is that the first block determines participants' internal criterion and baseline temporal expectations. Regarding speed, participants were most sensitive to changes in stimuli in the absence of a 'train' and in the 3-event condition. The absence of a salient event coupled with fewer events could have increased boredom, decreased vigilance and reduced sensitivity by diverting attention. Indeed, boredom is an important predictor of experiential passage of time (Martinelli & Droit-Volet, 2022a). Alternatively, the salience of an event may affect the speed of time more than duration due to hierarchical event segmentation (Zacks & Tversky, 2001). Just as the sensitivity decreased with the increasing event density following coarser segmentation levels (Zacks, Tversky, & Ier, 2001; Zacks & Tversky, 2001), the presence of a train could have yielded a higher-level scene parsing, resulting in a coarser segmentation into a pre-train and post-train episode potentially overshadowing the effect of finer events.

Altogether, we suggest, in agreement with event segmentation theories, that duration estimation (interval timing) derives from speed estimation. This hypothesis implies the stability of an internal updating process relying both on external event boundaries and on internal processes when clear boundaries are absent. The interplay between interval timing and the speed of time would be computationally linked through the rate of change, analogous to what is proposed in the spatial navigation system (Issa et al., 2020). Our current observations are limited in that both duration and speed estimates could result from a common dependency on objective duration. Nevertheless, our results hint at the fact that the temporal measure used in event segmentation studies essentially relies on a speed of time heuristics (i.e. rate of change) rather than interval timing. This observation provides an interesting novel link between time and memory processes.

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CRediT authorship contribution statement

Marianna Lamprou-Kokolaki: Conceptualization, Formal analysis, Investigation, Methodology, Software, Visualization, Writing – original draft. **Yvan Nédélec:** Conceptualization, Methodology, Writing – review & editing. **Simon Lhuillier:** Resources, Software, Writing – review & editing. **Virginie van Wassenhove:** Conceptualization, Funding acquisition, Methodology, Project administration, Supervision, Writing – review & editing.

Declaration of competing interest

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

Data availability

Data will be made available on request.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.concog.2024.103635.

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