Negative emotion reduces the temporal compression of events in episodic memory

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Publication status: Accepted for publication in *Cognition and Emotion.*

Draft date: April 24, 2025

Citation: Colson, C., Panneels, G., & D'Argembeau, A. (in press). Negative emotion reduces the temporal compression of events in episodic memory. *Cognition and Emotion*. https://doi.org/10.1080/02699931.2025.2501047

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Acknowledgements: This work was supported by the Fonds de la Recherche Scientifique-FNRS under Grant n° 40013479. Arnaud D'Argembeau is a Research Director at the Fonds de la Recherche Scientifique-FNRS, Belgium. We thank Damien Lesenfants for his help in computing the measure of objective complexity.

CRediT authorship contribution statement

Charline Colson: Methodology, Resources, Data curation, Formal analysis, Visualization, Writing - original draft.

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Arnaud D'Argembeau: Conceptualization, Methodology, Funding acquisition, Visualization, Supervision, Writing - original draft, Writing - review & editing.

Disclosure of interest

The authors report there are no competing interests to declare.

Abstract

Recent studies have revealed that the continuous flow of information that characterizes naturalistic events is temporally compressed in episodic memory, so that remembering an event generally takes less time than the duration of the past episode. However, the specific characteristics of an event that influence its temporal compression in memory remain poorly understood. In the present study, we examined the extent to which the negative valence of events impacts their rate of compression in memory representations. We conducted two experiments in which participants were instructed to mentally replay a series of videos depicting negative or neutral events. The results showed that the time taken to mentally replay a video, relative to the actual video duration, was significantly longer for negative than for neutral videos. These results suggest that negative emotion increases the sampling rate of units of experience that represent the course of events, leading to a lower compression of events in memory representations.

Keywords: episodic memory; temporal compression; negative emotion; videos

Introduction

Episodic memory enables us to mentally travel back in time to relive past events in vivid detail (Tulving, 2002). However, memories are not exact records of the past, but rather summary representations of events (Conway, 2009). Consequently, the time required to remember an event is generally shorter than the actual duration of the past episode, a phenomenon that has been referred to as the *temporal compression* of events in episodic memory (Jeunehomme & D'Argembeau, 2019, 2023). While recent studies have shed new light on this phenomenon (for review, see D'Argembeau et al., 2022), the specific characteristics of an event that influence its temporal compression in memory remain poorly understood. One dimension that could play a major role in this regard is the emotional value of the event, given the well-established effects of emotion on memory (Holland & Kensinger, 2010; Talmi, 2013). Nevertheless, the impact of emotion on the temporal structure of memory representations has received relatively little attention, and its effect on the temporal compression of events is unknown. The present study aims to fill this gap.

In our daily life, we are faced with a continuous stream of information that unfolds over time. A key question in episodic memory research is how this continuous stream is retained and structured in memory (Baldassano et al., 2017; Zacks, 2020). To address this issue, recent studies have examined the structure of memory representations for the unfolding of dynamic events—either real-world events or videos representing naturalistic events (Jeunehomme & D'Argembeau, 2019, 2020, 2023). A consistent finding has been that memories do not represent events as a continuous stream, but rather as a sequence of discrete experience units (i.e., slices of past experience) that includes temporal discontinuities, where less informative segments of the past episode are omitted (Jeunehomme & D'Argembeau, 2023). Consequently, memories contain gaps: some segments of prior experience are not represented, explaining why the act of remembering an event is generally shorter than its actual duration (Jeunehomme & D'Argembeau, 2019).

For the process of compression to function effectively, the most informative or significant moments of experience must be integrated into memories. Emotion could play a key role in this selection process. Memory is typically enhanced for emotional events compared to neutral ones. This effect has been demonstrated both in laboratory settings and for real-life events, using a wide range of paradigms and stimuli (for reviews, see Holland & Kensinger, 2010; LaBar & Cabeza, 2006; Talmi, 2013). Emotion affects episodic memory through various mechanisms that operate during encoding (Mather & Sutherland, 2011; Pourtois et al., 2013), consolidation (McGaugh, 2018), and retrieval (Kensinger & Ford, 2020). This memory enhancement is especially pronounced for negative events that elicit arousal (Kensinger, 2009). However, a memory trade-off effect has also been identified, especially for negative events, in which memory enhancement was observed for central aspects of events, while some peripheral details and contextual information were impaired (Holland & Kensinger, 2010; Mather & Sutherland, 2011). Emotion appears to have different effects on distinct types of contextual details, but it remains unclear which details exactly are affected (De Montpellier & Talmi, 2023; Petrucci & Palombo, 2021).

A fundamental contextual component of episodic memories is time (Eichenbaum, 2013; Tulving, 2002). The events we experience and remember take place over time, have a sequence and duration. Given their importance, recent research has explored the impact of emotion on these temporal aspects of episodic memory (Petrucci & Palombo, 2021). In studies assessing temporal-order memory (i.e., the ability to remember the order of occurrence of events across time), participants are instructed either to remember the sequence in which stimuli were presented and/or to judge which of two stimuli appeared first. Research has shown mixed effects of negative emotion, with some studies showing that it enhances temporal-order memory (Cliver et al., 2024; Dev et al., 2022; Riegel et al., 2023; J. Wang & Lapate, 2024), and others that it impairs it (Huntjens et al., 2015) or has no effect at all (De Montpellier & Talmi, 2023). This inconsistency across studies may be attributed to differences in the stimuli used (Petrucci & Palombo, 2021). Indeed, most studies using cohesive narratives (i.e., series of causally connected events; J. Chen & Bornstein, 2024), rather than unrelated items, have found an enhancement in temporal-order memory (Cliver et al., 2024; Dev et al., 2022).

Besides studies focusing on temporal order, other research has investigated the effects of emotion on the estimated duration of events. Numerous studies involving retrospective duration judgments have found that negative events are remembered as lasting longer than neutral events, suggesting a time dilation in memory (Petrucci & Palombo, 2021). To the extent that retrospective duration estimates are related to the amount of information stored in memory for an event (Ornstein, 1969; Block et al., 2010; Faber & Gennari, 2015), these longer estimates suggest that more information is stored in memory for negative events (Petrucci & Palombo, 2021). However, little is known about how the unfolding of emotional events is structured and represented in episodic memory. A recent study has shown that discrete items encoded in a sequence are judged to be closer in time when they involve negative compared to neutral stimuli, suggesting a *more compressed* representation of the sequence of events (J. Wang & Lapate, 2024). However, this study used static images as stimuli, so it remains unclear whether and how the representation of the unfolding of more naturalistic events is influenced by emotion. The current study aims to address this gap by investigating the effect of negative emotion on the temporal compression of events in memory representations.

Given the role of emotion in prioritizing information processing, we hypothesized that the unfolding of negative events would be sampled at a higher rate at encoding, so that their memory representations would contain more information per unit of time, resulting in lower compression rates. In other words, the duration of the mental replay of an event should be closer to the actual event duration for negative than for neutral experiences. To test this hypothesis, we measured the time taken by participants to mentally replay negative and neutral videos. We used videos because they are naturalistic stimuli that, like real-world events, unfold over time and possess an inherent temporal and causal structure (J. Chen & Bornstein, 2024; Jääskeläinen et al., 2021). For each video, we compared remembering duration to the actual length of the video to compute a compression rate (i.e., the ratio of the actual video duration to the duration of its mental replay) (Jeunehomme & D'Argembeau, 2023; Leroy et al., 2024).

We conducted two experiments to investigate the influence of negative emotion on the temporal compression of events in memory. In the first experiment, participants viewed each video individually, then immediately replayed it mentally and described it verbally. We predicted that the course of negative events would be less summarized in memory, resulting in a lower compression rate compared to neutral videos. The second experiment then sought to further investigate the effect of negative emotion on memory compression by presenting stimuli in a mixed list of negative and neutral videos, rather than in isolation, before performing the memory tasks. Research has shown that the effect of emotion is stronger with mixed lists of static stimuli (Talmi et al., 2019), and we hypothesized that this effect would extend to naturalistic stimuli. Consequently, we expected to observe an overall increase in memory compression rates in Experiment 2 compared with Experiment 1, but that the difference in compression rates between negative and neutral videos would be greater.

Experiment 1

In Experiment 1, participants were asked to mentally replay negative and neutral videos in a within-subjects design. The time they needed to remember each video was measured and compared to the actual video duration. We predicted that event compression rates in memory (i.e., the ratio of the actual video duration to the duration of its mental replay) would be larger for neutral videos than for negative videos. After the mental replay of each video, participants verbally described the content of their memories, and we used the length of these verbal descriptions as an estimation of the level of detail of memories.

Method

Participants

Participants were 34 adults (28 females, 5 males, and 1 undefined) aged between 18 and 30 years (M = 20.15, SD =2.2), who were recruited through a subject pool and word-of-mouth. This sample size was determined a priori to reach a statistical power of 80% (with an alpha of .05, two-tailed) to detect a statistically significant within-subjects difference, with a medium effect size (d = 0.50). Note that this was only an approximation as we analyzed data using mixed-effects modeling, which allows increasing statistical power by simultaneously considering all factors that potentially contribute to the understanding of the structure of the data: not only fixed-effects factors that are experimentally manipulated (in the present case, the emotional value of videos), but also covariates bound to the items (e.g., video duration; see Data cleaning and statistical analyses) (Baayen et al., 2008). To be eligible, participants were required not to take medications that could affect their attentional capacities and were not to suffer from psychological, psychiatric, or neurological disorders. All participants provided written informed consent and were warned that some videos might offend their sensibilities. The study was approved by Ethics Committee of the Faculty of Psychology of the University of Liège (ref.2324-034).

Materials

A total of 16 videos (8 negative, 8 neutral) were selected for use in this experiment. The selection process involved two phases: first, we identified a series of videos that met our criteria in validated databases; second, we conducted an online study in which these videos were assessed along various dimensions to help us finalize the selection of stimuli (see Supplementary Materials, for more detail about the selection process and validation study). To make an initial selection of stimuli, two independent researchers identified and examined 13 databases of emotional videos, from which 36 videos were selected. An online study ($n = 90$) was then conducted to obtain ratings of the valence, arousal, unusualness, unpredictability, and visual complexity of each video. This allowed us to select videos with minimal variance in ratings of valence and arousal to ensure a consistent emotional impact across participants, and to obtain ratings for additional video dimensions (unusualness, unpredictability, and visual complexity) that could potentially influence memory beyond emotion. In addition to the evaluation of videos by human observers, we assessed the objective visual complexity of the videos using a new image complexity metric (*R*spt) based on detectability suprathreshold (Durmus, 2020).

Based on the ratings obtained in the online study, a total of 16 out of the 36 videos were selected, essentially by selecting videos with the lowest variance in valence ratings and avoiding the use of videos depicting similar events (e.g., two videos showing a car accident). In addition, we took care to select negative and neutral videos that were matched in duration. Although we had initially planned to try to select negative and neutral videos matched on unusualness, unpredictability, and subjective visual complexity, this was not possible as the distribution of negative and neutral video ratings on these dimensions barely overlapped. However, we were able to select negative and neutral videos that were matched in objective visual complexity (both for mean and SD of complexity). Descriptive statistics for the final set of videos (8 negative, 8 neutral) are shown in Table 1. Stimuli are openly available in OSF at https://osf.io/kqj3v/.

Table 1

Characteristics of negative and neutral videos from the online validation study

Dimensions	Negative videos	Neutral videos
Duration (in sec)	25.9 (7.39)	25.8 (7.06)
Valence	83 (10.3)	10 (2.35)
Arousal	63 (4.16)	16 (3.88)
Unusualness	76 (10.5)	14 (8.21)
Unpredictability	70 (8.42)	15 (4.99)
Subjective complexity	58 (6.09)	43 (10.4)
Objective complexity (mean R_{spt})	144 (119)	181 (117)
Objective complexity (SD R_{spt})	40 (34)	37 (20)

Note. For each dimension evaluated in the online study, ratings were made using a visual analog scale ranging from 0 to 100 (anchors are specified in the Supplementary materials). For each dimension, ratings from all participants were first averaged for each video and means and SDs across videos were then calculated separately for negative and neutral videos. SDs are shown in parentheses.

Procedure

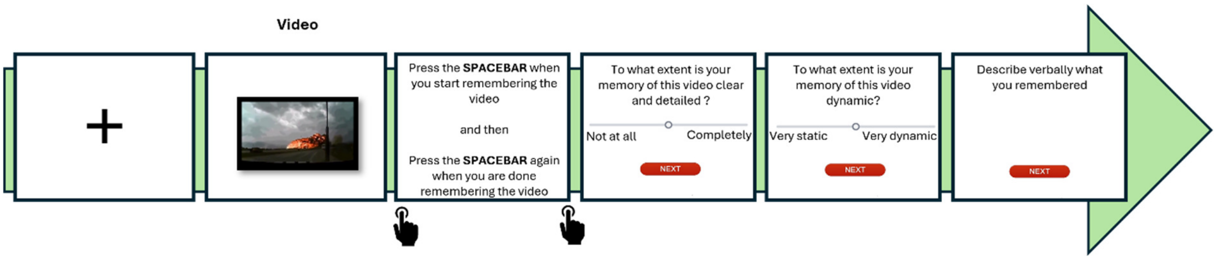
Participants first received a memory task in which they were asked to mentally replay each video. Then, they assessed the videos for valence, arousal, and other event dimensions. The two tasks were presented using E-Prime software version 3.0 (Schneider et al., 2012).

Memory task. Each trial began with the presentation of a 1-s fixation cross on the computer screen, followed by the presentation of a video (see Fig. 1). Participants were instructed to attentively watch the video. Immediately after the video ended, participants were instructed to mentally replay the unfolding of the depicted event in as much detail as possible, as if they were watching the video again in their minds. They were instructed to press the spacebar to indicate the start and end of their mental replay (Jeunehomme & D'Argembeau, 2019). The duration of mental replay was compared to the actual duration of the video to compute a temporal compression rate (i.e., the ratio of the actual video duration to the duration of mental replay). After their mental replay, participants rated their memory on visual analogue scales (VAS; ranging from 0 to 100) evaluating the level of detail (from not at all detailed to very detailed) and dynamism (from static to very dynamic) of their representation. Then, participants verbally described everything that had come to mind during their mental replay. Once this verbal description had been completed, the next trial with another video was presented. The videos were presented in random order. Before beginning the experiment, participants completed one practice trial (with a different video) to familiarize themselves with the task.

Video assessment task. After completing the memory task, participants watched each video again and assessed it along several dimensions. These dimensions were the same as in the online validation study (i.e., valence, arousal, unusualness, unpredictability, and visual complexity), with the addition of two new dimensions: memorability (from very forgettable to very memorable) and familiarity with the video (from never seen before to very familiar). The first dimension was included for exploratory purposes to investigate the extent to which negative videos were deemed more memorable, while the second dimension was assessed to exclude videos that had already been seen by participants. On each trial, participants watched a video and subsequently evaluated it based on each dimension using a VAS. A practice trial with another video (the same as for the practice trial of the memory task) was presented to familiarize participants with the rating procedure. Participants then viewed and rated the entire set of 16 videos in random order.

Figure 1

Illustration of a trial of the Memory Task in Experiment 1



Data cleaning and statistical analyses

Trials for which the video had already been seen by the participant on a previous occasion were excluded. When three or more videos had already been seen by a participant, the entire participant was excluded. This resulted in the exclusion of 14 negative trials and 1 neutral trial due to familiarity with the videos. In addition, trials with compression rates exceeding three standard deviations from the mean (M = 1.21, SD = 0.87) were excluded (Osborne, 2013), resulting in the removal of 9 trials; 6 of these trials came from a single participant, and his other values were also high, so we excluded this participant entirely. The reported analyses were conducted on 509 trials from 33 participants (note that the main results remained the same when all the data were included in the analyses).

Differences between negative and neutral videos were assessed using a series of linear mixed-effects models. First, we investigated the extent to which negative and neutral videos differed on each of the event dimensions that were rated by participants. We fitted separate models for each rated dimension (i.e., valence, arousal, unusualness, unpredictability, visual complexity, memorability, and complexity) using the type of video as predictor and the dimension as dependent variable.

Our main interest was then to examine the extent to which the rate of temporal compression of events during memory replay differed between negative and neutral videos. The distribution of temporal compression rates was right-skewed, so we first applied a log-transformation of compression rates for use in the statistical analyses (Benoit, 2011). We fitted a robust mixed-effects model with temporal compression rates as outcome, the type of video (negative vs. neutral) as predictor, and video duration as covariate. As video duration explains a large proportion of variance in compression rates (Leroy et al., 2024), it was included as a covariate in the model (as previously indicated, negative and neutral videos did not differ on average duration) to increase the precision of the effect of interest (i.e., the effect of video type; Walker, 2020). Not including this covariate could obscure the true effect of interest, as variance attributable to video duration would otherwise contribute to noise (ε) in the model, thereby reducing precision in estimating the impact of the type of videos on temporal compression.

Next, we calculated the length (number of words) of the verbal descriptions of memories to provide an estimate of the amount of detail in memory representations (Kyung et al., 2016). The distribution of this variable was also right-skewed, so we applied a log-transformation for use in the statistical analyses. First, we investigated differences between negative and neutral videos in the number of words reported by fitting a robust linear mixed-effects model with number of words as outcome, type of video as predictor and video duration as covariate. In addition, to check that our measure of temporal compression is indeed related to the level of detail of memories, we fitted a model with temporal compression rates as outcome, the number of words used to describe memories as predictor, and video duration as covariate.

Finally, we analyzed the subjective evaluations that participants made of their memories (i.e., ratings for detail and dynamism). Differences between negative and neutral videos were assessed by fitting two models: one predicting detail and the other predicting dynamism. Next, we examined the extent to which compression rates were predictive of the subjective evaluations of memories. To do so, we fitted two models with compression rates as predictor and the levels of detail and dynamism as outcomes.

All analyses were performed using the robustlmm package in R (Koller, 2016), and the parameters package (Lüdecke et al., 2020) was used to obtain uncertainty intervals (equal-tailed) and *p*-values (two-tailed) using a Wald *t*-distribution approximation. The type of video was included as a dichotomous predictor (with neutral videos as reference) and continuous predictors were cluster-mean centered (i.e., centered around each subject's own mean) to obtain an unbiased estimate of the within-subjects association between the predictor and the outcome. In all models, the maximal random structure justified by the design was used: a by-participant random intercept, a by-participant random slope, and a by-item (video) random intercept (Barr et al., 2013). In case the model failed to converge, we removed the correlation between random effects; if convergence issues persisted, we further simplified the model by removing random slopes that were estimated to be zero. All data and analysis code are available in OSF at https://osf.io/kqj3v/.

Results

Videos assessment

First, we examined differences in the characteristics of negative and neutral videos. Descriptive statistics for each dimension are shown in Table 2. As expected, negative videos were rated as more negative (b = 82.59, SE = 1.24, 95% CI [80.16, 85.02], t = 66.80, p <.001) and more arousing (b = 67.93, SE = 3.24, 95% CI [62.57, 74.29], t = 21, p <.001) than neutral videos. Negative videos were also rated as more unusual (b = 77.44, SE = 4.2, 95% CI [69.18, 85.70], t = 18.42, p <.001), more unpredictable (b = 62.04, SE = 5.36, 95% CI [51.51, 72.57], t = 11.57, p <.001) and more memorable (b = 61.78, SE = 3.34, 95% CI [55.21, 68.35], t = 18.48, p <.001) than neutral videos. There was no significant difference between negative and neutral videos for subjective complexity ratings (b = -8.11, SE = 12.12, 95% CI [-31.93, 15.71], t = - 0.67, p = 0.504).

Temporal compression

The primary aim of this study was to investigate the influence of negative emotion on the temporal compression of events in episodic memories. Temporal compression was measured as the ratio of the actual video duration to the duration of its mental replay. The data aggregated for each participant are shown in Figure 2. A robust linear mixed-effects model revealed that compression rates differed between the two types of videos, with negative videos being less compressed than neutral videos in memory representations (b = -0.13, SE = 0.06, 95% CI [-0.24, -0.02], t = -2.28, p = 0.023). Unsurprisingly, the effect of the covariate video duration was also significant, indicating that longer videos were more compressed than shorter ones (b = 0.02, SE = 0.004, 95% CI [0.02, 0.03], t = 6.2, p < .001).

Given that negative and neutral videos differed in ratings of unusualness and unpredictability, we included these two variables as covariates of no interest in separate models to determine if the difference in compression rates between the two types of videos remained statistically significant when these two dimensions were accounted for. The difference in compression rates between negative and neutral videos were no longer statistically significant when adding unusualness (b = -0.12, SE = 0.07, 95% CI [-0.26, 0.02], t = -1.66, p = 0.098) or unpredictability (b = -0.05, SE = 0.06, 95% CI [-0.18, 0.07], t = -0.80,

p = 0.422) ratings to the model; video duration was the only significant predictor of compression rates in these models.

Next, we examined the number of words used to describe memories as an estimate of their level of detail. Memories of negative videos were described using more words than memories of neutral videos (b = 0.26, SE = 0.09, 95% CI [0.08, 0.44], t = 2.90, p = 0.004). Furthermore, we found that the number of words used to describe memories predicted temporal compression rates, with higher compression rates observed when fewer words were used (b = -0.0023, SE = 0.00035, 95% CI [-0.0033, -0.0012], t = -6.69, p < .001).

Subjective evaluations of memory

Finally, we examined the subjective evaluations of the level of detail and dynamism of memories. The models examining differences in these evaluations between the two types of videos revealed that memories of negative videos were rated as more detailed (b = 12.48, SE = 3.62, 95% CI [5.37, 19.59], t = 3.45, p < .001) and more dynamic (b = 11.14, SE = 3.14, 95% CI [4.96, 17.32], t = 3.54, p < .001) than memories of neutral videos. Compression rates did not significantly predict the subjective evaluation of the dynamism of memories (b = -0.56, SE = 2.40, 95% CI [-5.28, 4.16], t = -0.23, p = 0.815), nor their level of detail (b = 0.35, SE = 2.28, 95% CI [-4.13, 4.84], t = 0.16, p = 0.877).

Table 2

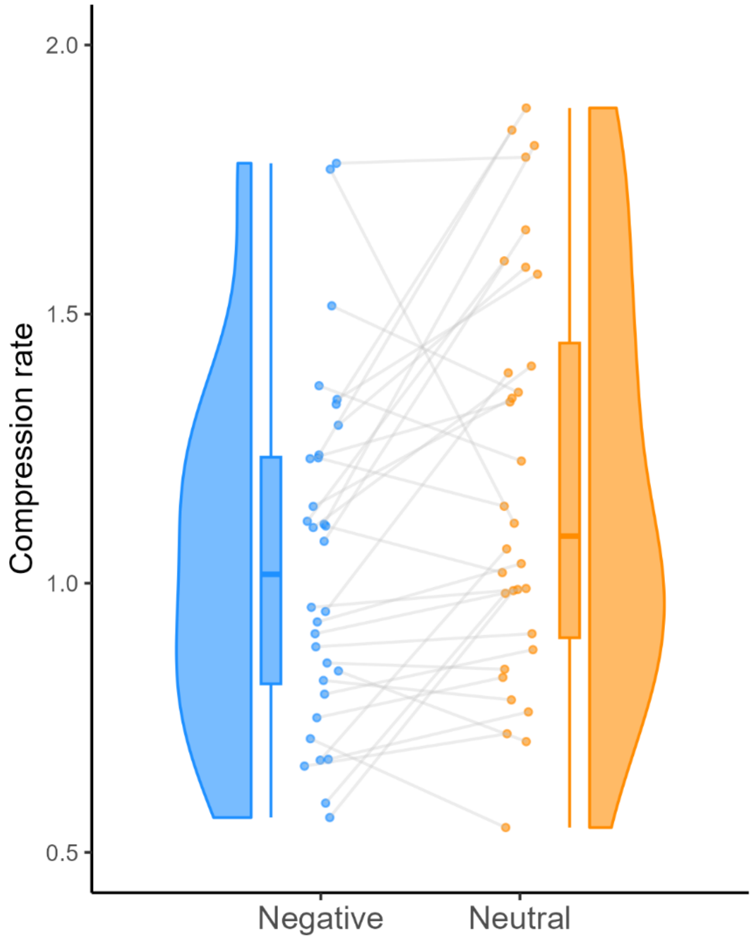
Means (and standard deviations) of ratings for negative and neutral videos in Experiment 1

Dimensions	Negative videos	Neutral videos
Valence	77.1 (17.1)	3.37 (5.27)
Arousal	68.9 (17.7)	6.9 (8.66)
Unusualness	80.9 (14)	12.9 (10.8)
Unpredictability	65.3 (16)	10.2 (9.27)
Subjective complexity	39.9 (13.1)	48.7 (12.9)
Memorability	64.3 (13.6)	10.9 (17.3)

Note. All dimensions were rated on a VAS ranging from 0 to 100. For each dimension evaluated, we first averaged the ratings of negative and neutral video for each participant. Then, we calculated the means and standard deviations across all participants, separately for negative and neutral videos.

Figure 2

Compression rates for negative and neutral videos in Experiment 1



Note. Data points represent compression rates aggregated for each participant.

Discussion

As predicted, we found that memories of negative events were less compressed than memories of neutral events. Furthermore, verbal descriptions of memories included more words for negative than neutral events, and compression rates were predicted by the number of words used to describe memories, suggesting that our measure of temporal compression reflects the amount of details within memory representations. Negative emotion also impacted the subjective experience of remembering: memories of negative events were rated as more detailed and dynamic than memories of neutral events.

Overall, Experiment 1 provides initial evidence that negative emotion is associated with less compressed representations in memory. However, the difference in compression rates between negative and neutral videos was relatively small (see Figure 2) and was no longer statistically significant when accounting for video differences in unusualness and unpredictability. This suggests that the observed difference in compression rates between negative and neutral videos could be due to differences in the event unpredictability and unusualness—two dimensions known to influence memory (Bein et al., 2023; Finley & Brewer, 2024). However, these dimensions tend to be an integral part of real-life emotional events (Cahill & McGaugh, 1995), making it challenging to disentangle their effects from those of emotion itself.

Experiment 2

Although Experiment 1 showed that negative emotion decreased the temporal compression of events in memory, the effect was relatively small. However, it is likely that the paradigm we used, in which each video was recalled individually and immediately after its presentation, minimized the effect of negative emotion on memory. Indeed, it has been shown that the effect of emotion is stronger when stimuli are presented in lists that include both emotional and neutral items (Talmi et al., 2019), and is also stronger after a longer delay (Williams et al., 2022). Therefore, in Experiment 2, we sought to further examine the effect of negative emotion on memory compression using a mixed-list design in which all videos were presented before their memory was assessed. This modification in the experimental design also introduced a short delay between the encoding and retrieval of each video, which may enhance the effect of emotion (Kensinger, 2009). Furthermore, whereas in Experiment 1, participants were necessarily aware that their memory was being tested (since they had to remember each video immediately after its presentation), in Experiment 2, encoding was incidental, in order to approximate the way events are typically encoded in everyday life. We expected to replicate the results of Experiment 1 and hypothesized that the modifications included in Experiment 2 would enhance the effect of negative emotion on the temporal compression of events in episodic memories.

Method

Participants

As in Experiment 1, we recruited 34 participants through a subject pool and word-of-mouth. The sample included 22 females and 12 males aged between 18 and 30 years (M = 20.8, SD =2.05). All participants provided written informed consent and the study was approved by Ethics Committee of the Faculty of Psychology of the University of Liège (ref.2324-034).

Materials and procedure

The same set of videos as in Experiment 1 was used. As in Experiment 1, the experimental procedure also included two phases: a memory task and a video evaluation task. The primary difference was that the entire set of 16 videos (8 neutral and 8 negative) was viewed before memory was tested. During encoding, all videos were presented in random order and participants were instructed to attentively watch each video. After viewing all the videos, they then received the memory task. On each trial, a verbal cue corresponding to one of the 16 videos was first presented (e.g., plane crash). Participants had to identify the corresponding video and then performed the same memory task as Experiment 1 (mental replay, subjective assessment, and verbal recall) for that specific video. For the subjective assessment, participants rated their memory in terms of detail and dynamism (as in Experiment 1), and we added an evaluation of the difficulty in remembering the unfolding of the event depicted in the video (ranging from 'not difficult at all' to 'very difficult'). The verbal cues corresponding to each video were presented in random order.

After completing the memory task for all the videos, participants received the video assessment task, which followed the same procedure as in Experiment 1. The evaluated dimensions were the same, with the addition of a question assessing the participant's familiarity with similar videos (ranging from "I have never seen a similar video before" to "I often watch this type of video"). This was added as participants might not have seen the exact video but could be accustomed to watching similar ones.

Data cleaning and statistical analysis

The same exclusion criteria as in Experiment 1 were applied: trials involving videos that had already been seen by the participants were excluded, and participants were excluded if they had seen three or more videos. In addition, some participants failed to recall some videos when provided with the corresponding verbal cues and these trials were also excluded. As a result, 23 negative trials were excluded due to familiarity with the video and 23 neutral trials were excluded due to failure to remember the video. Additionally, trials with compression rates exceeding three standard deviations from the mean (M = 1.96, SD = 1.46) were excluded (Osborne, 2013), resulting in the removal of 7 trials. The reported analyses were thus conducted on 491 trials from 34 participants (note that the main results remained the same when all the data were included in the analyses).

As in Experiment 1, the distributions of temporal compression rates and of the number of words used in verbal recall were right-skewed, so we applied a log-transformation to these variables for use in statistical analyses. The same statistical analyses as in Experiment 1 were performed. All data and analysis code are available in OSF at https://osf.io/kqj3v/.

Results

Videos assessment

The differences in the evaluated characteristics of negative and neutral videos replicated those found in Experiment 1. Negative videos were rated as more negative (b = 81.12, SE = 3.02, 95% CI [75.19, 87.06], t = 26.89, p <.001), more arousing (b = 63.21, SE = 4.31, 95% CI [54.75, 71.67], t = 14.68, p <.001), more unusual (b = 68.86, SE = 5.82, 95% CI [57.42, 80.30], t = 11.83, p <.001), more unpredictable (b = 46.10, SE = 5.46, 95% CI [35.37, 56.83], t = 8.44, p <.001), and more memorable (b = 53.74, SE = 4.26, 95% CI [45.36, 62.12], t = 12.6, p <.001) than neutral videos. Additionally, familiarity with similar videos was rated as higher for negative videos than for neutral ones (b = 20.44, SE = 4.39, 95% CI [11.81, 29.07], t = 4.65, p <.001). As in Experiment 1, no significant difference was observed between negative and neutral videos in subjective complexity ratings (b = -3.41, SE = 10.71, 95% CI [-24.45, 17.62], t = -0.32, p = 0.75). Descriptive statistics for each dimension are presented in Table 3.

Temporal compression

As in Experiment 1, we conducted a mixed-effects model to examine the impact of the type of videos (negative vs. neutral) on memory compression rates (the ratio of the actual video duration to the duration of its mental replay), with video duration included as covariate. We found that negative videos were less compressed in memory representations than neutral videos (b = -0.32, SE = 0.08, 95% CI [-0.48, -0.16], t = -3.97, p < .001). The data aggregated for each participant are shown in Figure 3. Additionally, longer videos were more compressed than shorter ones ($b = 0.03$, SE = 0.0052, 95% CI [0.02, 0.04], $t = 5.15$, $p < .001$).

Given that negative and neutral videos differed in ratings of unusualness, unpredictability and familiarity with similar videos, these variables were included as covariates of no interest in separate models to assess whether negative emotion still significantly impacts compression rates when these variables are controlled for. The difference in compression rates between negative and neutral videos remained statistically significant when adding unusualness ($b = -0.33$, SE = 0.09, 95% CI [-0.51, -0.14], $t = -3.50$, $p < .001$), unpredictability ($b = -0.32$, SE = 0.09, 95% CI [-0.49, -0.15], $t = -3.73$, $p < .001$) and familiarity with similar videos ($b = -0.31$, SE = 0.08, 95% CI [-0.47, -0.15], $t = -3.72$, $p < .001$) as a covariate in separate models. Furthermore, the difference in compression rates between negative and neutral videos also remained statistically significant ($b = -0.32$, SE = 0.10, 95% CI [-0.51, -0.12], $t = -3.15$, $p = 0.002$) when all three variables were added as covariates in the same model.

The analysis of the number of words used to describe memories replicated the results of Experiment 1: memories of negative videos were described using more words than memories of neutral videos ($b = 0.47$, SE = 0.13, 95% CI [0.22, 0.73], $t = 3.64$, $p < .001$), and compression rates were higher when fewer words were used ($b = -0.0025$, SE = 0.00035, 95% CI [-0.003, -0.002], $t = -7.25$, $p < .001$).

Following a reviewer’s suggestion, we also examined whether participants' memory descriptions contained errors. Each description was carefully reviewed and compared to the corresponding video. Out of the 491 trials, 81 contained errors (39 for neutral videos and 42 for negative videos). However, most of these errors were minor and concerned mistakes in the color of an object (e.g., describing a garment as grey rather than black) or confusions of similar items (e.g., mentioning a bowl instead of a glass). A few trials contained inversions in the precise order of events, but these were rare (9 trials). Only two trials involved the addition of elements that were not present in the video. Importantly, we re-ran all the analyses excluding the trials containing errors, and the results remained unchanged.

Subjective evaluations of memory

Memories of negative videos were rated as more detailed (b = 23.63, SE = 4.86, 95% CI [14.09, 34.18], t = 4.86, p < .001), more dynamic (b = 21.39, SE = 4.36, 95% CI [12.82, 29.96.03], t = 4.91, p < .001), and less difficult to remember (b = -21.63, SE = 4.23, 95% CI [-29.94, -13.32], t = -5.11, p < .001) than memories of neutral videos. Given this latter result, we included difficulty as covariate in the model predicting compression rates to determine if the effect of the type of videos remained statistically significant. We found that both difficulty (b =0.0016, SE =0.0006, 95% CI [0.0006, 0.0004], t = 2.18, p = 0.008) and type of videos (b = -0.29, SE = 0.08, 95% CI [-0.45, -0.13], t = -3.56, p < .001) were significant predictors of compression rates, suggesting that the two predictors have independent effects.

Next, we investigated the extent to which compression rates predict the subjective evaluations of memories. We observed that memories with higher compression rates were rated as less detailed (b = -5.25, SE = 1.63, 95% CI [-8.46, -2.04], t = -3.21, p < .001) and less dynamic (b = -5.96, SE = 1.42, 95% CI [-8.75, -3.17], t = -4.20, p < .001). Moreover, compression rates predicted difficulty ratings (b = 5.30, SE = 1.82, 95% CI [1.71, 8.88], t = 2.90, p = 0.004), with higher compressions rates being associated with a higher difficulty to remember the unfolding of events.

Table 3

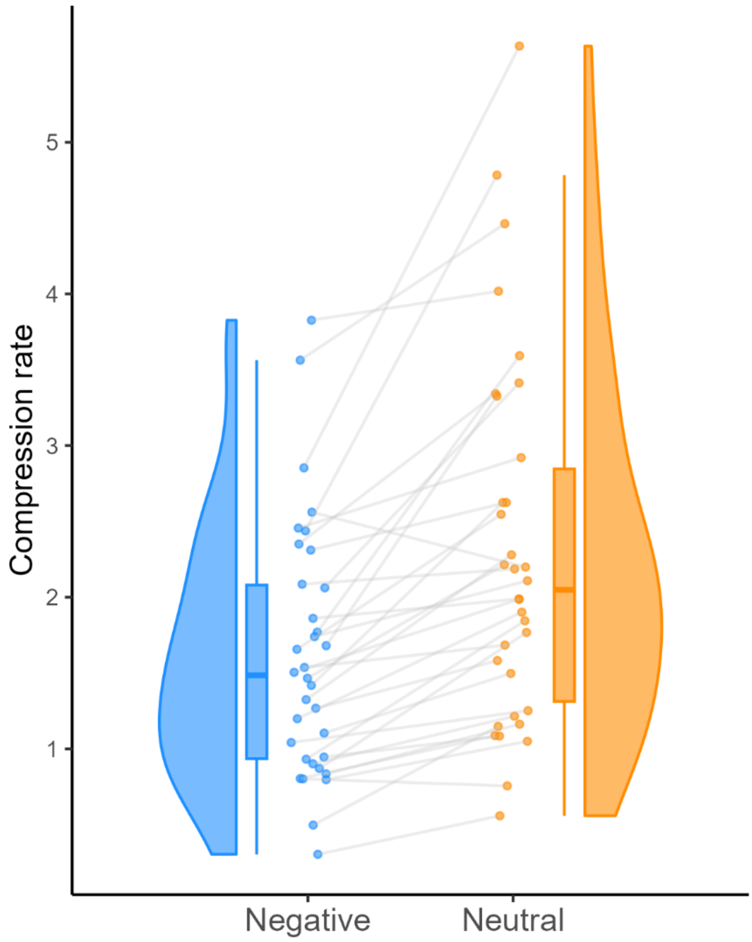
Means (and standard deviations) of dimensions for negative and neutral videos in Experiment 2

Dimensions	Negative videos	Neutral videos
Valence	76.2 (20.3)	3.36 (4.56)
Arousal	64 (25.6)	7.4 (10.1)
Unusualness	82.3 (17.9)	18.9 (15)
Unpredictability	54.7 (20.6)	10.7 (8.38)
Subjective complexity	42.1 (16.4)	44.6 (17.5)
Memorability	68.1 (20.7)	20.5 (17.8)
Familiarity with similar videos	45.1 (21.8)	26.9 (14.4)

Note. All dimensions were rated on a VAS ranging from 0 to 100. For each dimension evaluated, we first averaged the ratings for each participant for negative and neutral videos. Then, we calculated the means and standard deviations across all participants, separately for negative and neutral videos.

Figure 3

Compression rates for negative and neutral videos in Experiment 2



Note. Data points represent compression rates aggregated for each participant.

Comparison between Experiments 1 and 2

We expected that the modifications in the experimental design introduced in Experiment 2 would lead to a stronger effect of negative emotion on memory compression. To formally test whether this was the case, we analyzed the combined data of the two experiments and investigated whether there was a significant interaction between the effects of the type of video and of the experiment on our memory measures. We fitted separate models with compression rates, number of words used to describe memories, and subjective evaluations (level of detail and dynamism) as outcomes, and type of videos, experiment, and their interaction as predictors.

For compression rates, we found a main effect of the type of video (b = -0.22, SE = 0.06, 95% CI [-0.34, -0.10], t = -3.50, p < .001) and a main effect of experiment (b = 0.48, SE = 0.10, 95% CI [0.29, 0.68], t = 4.83, p < .001). Specifically, negative videos were less compressed than neutral ones, and compression rates were higher in Experiment 2 than in Experiment 1. Additionally, there was a significant interaction between type of video and experiment (b = -0.19, SE = 0.06, 95% CI [-0.31, -0.08], t = -3.35, p < .001), showing that the effect of emotion on compression rates was stronger in Experiment 2 than in Experiment 1 (see Fig. 4A).

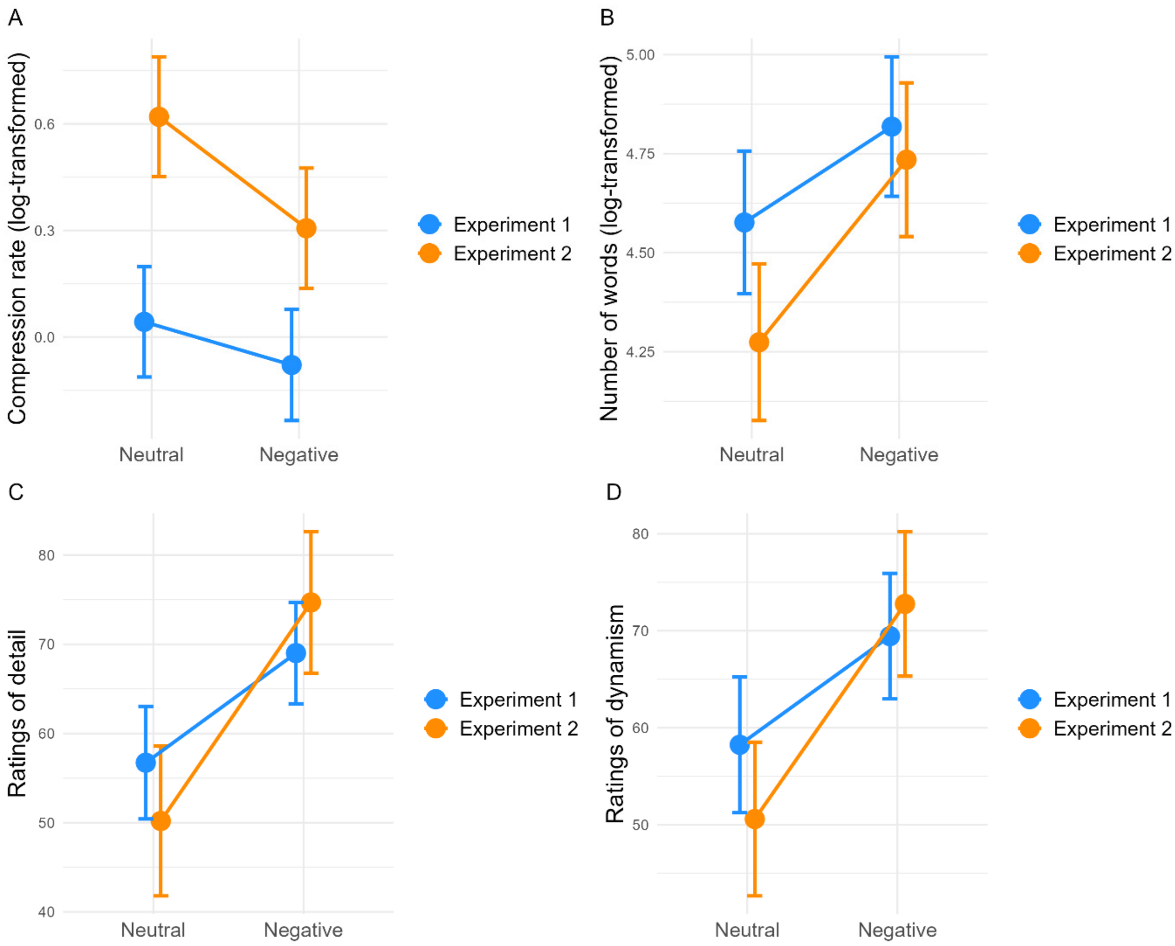
For the number of words used to describe memories, we found a main effect of condition with more words used for negative videos (b = 0.35, SE = 0.08, 95% CI [0.19, 0.51], t = 4.28, p < .001). The main effect of experiment was not significant (b = -0.19, SE = 0.11, 95% CI [-0.40, 0.02], t = -1.80, p = 0.072), but there was a significant interaction between the type of video and experiment (b = 0.22, SE = 0.05, 95% CI [0.12, 0.32], t = 4.34, p < .001). This interaction indicated that the effect of emotion on the number of words used to describe memories was stronger in Experiment 2 than in Experiment 1 (see Fig. 4B).

Finally, we found a main effect of the type of video on both ratings of detail (b = 18.40, SE = 3.89, 95% CI [10.77, 26.03], t = 4.73, p < .001) and dynamism (b = 16.70, SE = 3.20, 95% CI [10.42, 22.97], t = 5.22, p < .001), with memories of negative videos being rated as more detailed and dynamic. No main effect of experiment was found for ratings of detail (b = -0.43, SE = 3.41, 95% CI [-7.12, 6.27], t = -0.13, p = 0.90) or dynamism (b = -2.17, SE = 4.13, 95% CI [-10.26, 5.93], t = -0.53, p = 0.599) but there was an interaction between the type of the video and experiment for both ratings of detail (b = 12.21, SE = 4.49, 95% CI

[3.40, 21.02], $t = 2.72$, $p = 0.007$; see Fig. 4C) and dynamism (b = 10.98, SE = 4.44, 95% CI [2.27, 19.70], $t = 2.47$, $p = 0.014$; see Fig. 4D). The effect of negative emotion on subjective ratings was stronger in Experiment 2 than in Experiment 1. Additional analyses comparing the dimensions of unpredictability and unusualness between Experiments 1 and 2 are presented in in the Supplementary materials.

Figure 4

Interactions between type of video and experiment



Note. The graphs display the estimated marginal means for compression rate (A), number of words used to describe memories (B), ratings of detail (C) and dynamism (D), with the type of video, experiment and their interaction as predictors. Error bars represent 95% confidence intervals.

Discussion

Experiment 2 replicated and extended the main results of Experiment 1. As in Experiment 1, we found that negative events were less compressed than neutral events. However, this effect was stronger than in Experiment 1 and remained significant after accounting for differences in unusualness and unpredictability between events. The analyses of the length of verbal descriptions also replicated findings of Experiment 1, more words being used to describe memories of negative events. In addition, we found that memories of negative events were perceived as more detailed, more dynamic and less difficult to remember than memories of neutral events. Direct comparisons between experiments confirmed that these effects of negative emotion were stronger in Experiment 2 than in Experiment 1.

General Discussion

While recent studies have revealed that the continuous flow of information that characterizes naturalistic events is temporally compressed in episodic memory, the precise characteristics of an event that influence its rate of compression remain poorly understood. In the present study, we examined the extent to which memory compression is influenced by the negative valence of events. We conducted two experiments in which participants were instructed to mentally replay a series of videos depicting neutral or negative events. The results showed that the duration of mental replay, relative to the actual video length, was significantly longer for negative videos than for neutral ones, demonstrating that negative events were less compressed in memory. Consistently, verbal descriptions of memories contained more information for negative than neutral videos.

The main results of the two experiments indicate that the course of negative events is less summarized in memory than that of neutral events. Previous research has shown that memory is generally enhanced for emotional compared to neutral events (Holland & Kensinger, 2010; LaBar & Cabeza, 2006; Talmi, 2013). However, this enhancement is not uniform across all aspects of emotional events. For example, while memory is strengthened for central details of emotional stimuli, memory for peripheral or contextual details can be impaired (Kensinger et al., 2007; Mather & Sutherland, 2011). The specific contribution of the present study is to demonstrate that negative emotion influences memory for the unfolding of events. Previous research has shown that episodic memories summarize the course of events in the form of a sequence of event segments that correspond to the most informative parts of the sensory stream, while omitting other (less informative) parts of events (Jeunehomme & D'Argembeau, 2023). The present results suggest that negative emotion influences this internal structure of memory representations, by increasing the sampling rate of the units of experience that make up memories. Memories of negative events contain a greater density of information per unit of time when the unfolding of the event is represented.

Our results provide a potential explanation for the impact of negative emotion on retrospective assessment of event duration that has been observed in previous research (Petrucci & Palombo, 2021). The retrospective estimation that negative events lasted longer (Anderson et al., 2007; Campbell & Bryant, 2007; Li & Lapate, 2024; Özgör et al., 2018; Pollatos et al., 2014; Safi et al., 2023) could be due to the fact that people form a more detailed representation of the temporal course of negative experiences, as shown by the present results. Indeed, retrospective evaluation of duration is related to the amount of information stored in memory (Block et al., 2010) and the density of recalled moments of prior experience (Jeunehomme & D'Argembeau, 2019). In addition, a finer representation of the internal structure and unfolding of negative events could also explain why the temporal order of elements that constituted these events is better remembered (Cliver et al., 2024; Dev et al., 2022; Riegel et al., 2023; J. Wang & Lapate, 2024).

What mechanisms underlie the impact of negative emotion on memory for the temporal unfolding of events? A first possibility is that the reduced temporal compression of negative events in memory is due to attentional effects occurring during the perception of events. Research has shown that emotion increases attention (Mather & Sutherland, 2011), improving the encoding of events in memory (Petrucci & Palombo, 2021). Therefore, it could be that enhanced attention during the unfolding of negative events increases the sampling rate of information that is encoded in memory over time. A second potential mechanism would be that negative emotion influences how ongoing experience is segmented. In daily life, we segment the continuous flow of information into meaningful events and sub-events, which are temporally defined by the perception of event boundaries (Clewett et al., 2019; Kurby & Zacks, 2008). These event segments form the units of experience that constitute episodic memories (D'Argembeau et al., 2022). Events that are segmented into finer units are less compressed in memory, and segments of time around event boundaries are more likely to be recalled (Jeunehomme & D'Argembeau, 2020). Segmentation points (i.e., event boundaries) can be identified when a change in the external environment occurs, such as a change in location, action, people, and so on (Kurby & Zacks, 2008). However, internal changes, such as emotional fluctuations, may also play a role in the perception of event boundaries (Wang et al., 2024). Therefore, it could be that negative emotion increases the segmentation of events, which in turn may reduce temporal compression in memory representations. Although to our knowledge no study has definitively shown that emotional events are segmented in a finer-grained way, recent studies indicate that emotional shifts evoke event boundaries (R. Chen & Swallow, 2024; McClay et al., 2023). Furthermore, it has been found that emotional stimuli have behavioral effects on memory and attention that are similar to those of event boundaries:

they enhance item recognition, increase attention, and improve item-source memory for contextual details (Clewett & McClay, 2024). Collectively, these findings suggest that negative events could be segmented into finer sub-events compared to neutral events, resulting in a higher density of experience units formed in memory, longer mental replay time and, consequently, lower compression rates when recalling the unfolding of events.

The results of Experiment 1 demonstrate that the influence of negative emotion on the temporal structure of episodic memories is already established after the initial formation of the memory trace (i.e., when events are mentally replayed immediately after their perception). In addition, the higher emotional effect observed in Experiment 2, compared with Experiment 1, suggests that, while the effect of negative emotion on temporal compression is in part due to mechanisms occurring during the initial encoding of the event (e.g., heightened attention, event segmentation), additional (post-encoding) mechanisms are also involved. One likely candidate is memory consolidation. In Experiment 2, short delays were introduced between encoding and retrieval, whereas in Experiment 1, participants mentally replayed the videos immediately after their perception. Previous studies have shown that, although the effect of emotion on memory is observed after a short delay (Talmi, 2013), its mnemonic advantage increases with longer delay (McGaugh, 2018; Yonelinas & Ritchey, 2015). Another factor that differentiated Experiments 1 and 2 is the presentation of stimuli in mixed lists. Previous research has established that the effect of emotion is stronger when stimuli are presented in mixed lists comprising both emotional and neutral stimuli (Talmi et al., 2019). In Experiment 2, the fact that negative and neutral videos were presented in a mixed list could have led to an attentional prioritization of negative events during encoding, and thus the formation of more robust memory traces. Lastly, another difference between Experiments 1 and 2 is related to the encoding procedure. While Experiment 1 involved an intentional encoding paradigm, in Experiment 2 participants were unaware that their memory would be tested (i.e., incidental encoding). This change in the encoding condition could play a role, as intentional encoding could reduce or even eliminate the mnemonic advantage for some aspects of emotional events (D'Argembeau & Van Der Linden, 2004; Petrucci & Palombo, 2021). Future studies manipulating these three factors separately—the presentation of stimuli in a mixed list, the inclusion of a short delay, and incidental encoding—will need to be conducted to determine more precisely which specific mechanisms contribute to the effect of negative emotion.

While the present study shows that negative emotion reduces the temporal compression of events in memory, it remains to be determined which specific dimensions of negative events contribute to this effect. At a fundamental level, emotion can be conceptualized within a two-dimensional space characterized by valence (the degree to which an affect is pleasant or unpleasant) and arousal (the extent to which an affect is associated with subjective or physiological activation) (Barrett & Russell, 1999). It is well established that both dimensions contribute to emotional memory enhancement through distinct cognitive and neural processes (Kensinger & Corkin, 2004). However, the specific contribution of valence and arousal on temporal memory (i.e., retrospective duration evaluation, temporal source, and temporal order) remains unclear (Petrucci & Palombo, 2021), with some studies showing valence-specific processes (e.g., Campbell & Bryant, 2007), and others suggesting arousal-specific processes (Frederickx et al., 2013; Huntjens et al., 2015; Özgör et al., 2018). Future studies on temporal compression should independently manipulate valence and arousal to identify their respective effects. In addition, it would be interesting to use continuous emotion ratings (R. Chen & Swallow, 2024; Li & Lapate, 2024; McClay et al., 2023) during the perception of events to examine whether fluctuations of emotion over time can predict which parts of events are remembered and which are omitted. One could hypothesize that moments occurring just after a peak in emotional intensity will be better remembered, due to a 'forward-favouring' in temporal associations (i.e., more strongly encoded associations between negative stimuli and subsequent neutral stimuli) (Bogdan et al., 2023; Dunsmoor et al., 2022). It should also be noted that some researchers have argued that discrete emotions may have unique effects on memory (Droit-Volet, 2013; for review, see Todd et al., 2020). Therefore, specific emotions such as anger and fear may have different effects on the temporal compression of events in memory representations, a possibility that should be investigated in future studies. In addition, the present study focused on the effects of negative emotion, so the results would not necessarily extend to positive emotion. In fact, while the influence of negative emotion on the temporal aspects of episodic memory is relatively well established, the effects of positive events are less clear (Petrucci & Palombo, 2021).

Another important finding of the present study is that memories of negative events were perceived as more detailed, more dynamic and less difficult to remember than memories of neutral events. These results are consistent with previous studies showing that emotion enhances subjective aspects of memory, such as vividness and confidence (Comblain et al., 2005; Kensinger & Corkin, 2003). Some studies have found a dissociation between the influence of emotion on the subjective qualities of memories and objective memory measures, with emotional events being recalled with a greater sense of recollection and confidence, but not necessarily with greater precision or accuracy (for review, see Holland & Kensinger, 2010). However, in the present study, we found that objective measures of memory compression based on response times were aligned with subjective aspects of memories. Indeed, our measure of compression rates was a significant predictor of subjective memory evaluations, suggesting that the temporal representations of the dynamic unfolding of events contributed to the subjective quality of memories.

Another avenue for future research would be to investigate potential individual differences in the effect of negative emotion on memory compression. Indeed, the extent to which memory is enhanced for emotional events is not uniform across individuals (Kensinger, 2009). For instance, individuals with higher levels of anxiety are more likely to recall negative events in greater detail due to attentional bias (Mathews & MacLeod, 2005; Nørby, 2018). In the context of temporal memory, individuals with higher state anxiety exhibit greater impairment in temporal-order memory for emotional stimuli (Huntjens et al., 2015). Moreover, heightened dispositional negativity is associated with a dilation in the remembered duration of negative events (Li & Lapate, 2024). Given these findings, it would be interesting to examine whether individuals with higher anxiety exhibit less temporal compression in their memories for emotional events, and to investigate the underlying mechanisms.

A potential limitation of the present study is that although we sought to match the characteristics of negative and neutral videos as closely as possible, the two types of videos differed in some dimensions other than valence and arousal, notably unusualness and unpredictability. These factors are intrinsic to real-life emotional events (Cahill & McGaugh, 1995), and thus are difficult to control experimentally. Yet, controlling statistically for their potential impact on memory compression suggests that these factors do not entirely account for the observed difference in compression rates between negative and neutral videos. In the first study, after accounting for these covariates, the effect of negative emotion on the compression rate was no longer statistically significant. However, in Experiment 2, the difference between the two types of videos remained significant. This suggests that, at least in some conditions, negative emotion affects temporal compression independently of unpredictability and unusualness.

In conclusion, the present study shows that negative emotion modulates the temporal compression of events in episodic memory, with the dynamic unfolding of negative experiences being less summarized than that of neutral events. This suggests that the continuous stream of experience is sampled at a higher rate for negative events, leading to memory representations that contain a greater density of information per unit of time. Future research should focus on the underlying cognitive mechanisms during the initial encoding of events (i.e., attention and segmentation), as well as during consolidation and retrieval.

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Supplementary materials

Supplementary information about the selection of video stimuli

A total of 16 videos (8 negative, 8 neutral) were selected for use in this experiment. The selection process involved two phases: first, we identified a series of videos that met our criteria in validated databases; second, we conducted an online study in which these videos were assessed along various dimensions to help us finalize the selection of stimuli.

Video pre-screening. To make an initial selection of stimuli, two independent researchers identified and examined 13 databases of emotional videos (see Table S1). In addition, we searched on YouTube to identify additional relevant videos. The video selection criteria were: (1) emotional valence, selecting exclusively videos rated as neutral or negative; (2) video duration, excluding videos lasting less than 10 seconds (as recent data suggests that memory compression emerges when events last around 9 seconds; Leroy et al., 2024); (3) excluding videos from commercial films (to avoid familiarity with the stimuli); (4) absence of speech (so that the event can be understood without sound); (5) continuity of events within the video, avoiding cuts or shot changes; and (6) absence of unrealistic elements (e.g., monsters, horror dolls). No specific criteria were applied regarding the thematic content of the videos. Based on these criteria, 36 videos were selected from the databases DEVO (Ack Baraly et al., 2020), ADVOS (Gnacek et al., 2022), OpenLav (Israel et al., 2021), Mix Film Clip Library (Samson et al., 2016), and YouTube. Technical parameters of the 36 videos were standardized using DaVinci Resolve Studio 17 software (Blackmagic Design Pty. Ltd.): all videos were converted to MP4 format, with a resolution of 720x480 pixels, encoded with H.264 codec and a frame rate of 24 frames per second. When the video involved sound, it was removed. Furthermore, DaVinci Resolve Studio 17 and Hitpaw Watermark Remover were used to eliminate overlays (e.g., text, logos, timestamps) displayed on some videos, to prevent subjects from being distracted by them while viewing the videos. The selected videos ranged from 10 to 50 seconds in duration.

Video assessment. An online study was then conducted to assess the valence, arousal, unusualness, unpredictability, and visual complexity of the 36 videos. The aims of the study were twofold: (1) to select videos with minimal variance in ratings of valence and arousal to ensure a consistent emotional impact across participants; and (2) to obtain ratings for additional video dimensions (unusualness, unpredictability, and visual complexity) that could potentially influence memory beyond emotion, in an attempt to select negative and neutral videos that are matched as closely as possible on non-emotional variables. The dimension of unpredictability refers to prediction errors (i.e., inconsistency between what was expected and what happened) and the dimension of unusualness refers to the familiarity of events; both dimensions are known to influence memory (Bein et al., 2023; Finley & Brewer, 2024).

Participants were recruited on Prolific.ac (Palan & Schitter, 2018). A total of 92 participants were tested, but 2 of them were excluded due to a technical issue (i.e., they were presented with the same video twice). The final sample included 90 healthy young adults (41 female, 48 male, 1 other; mean age = 29 years, SD = 4; mean of education = 14.5 years, SD = 4.22) residing in the U.S. or U.K., with English as their first language. All participants provided informed consent and were warned that some videos might offend their sensibilities. The study was approved by the Ethics Committee of the Faculty of Psychology of the University of Liège (ref.2324-034).

The experiment was conducted using the Gorilla experiment builder (Anwyl-Irvine et al., 2020). After providing informed consent and demographic information, participants received instructions and completed a trial test with a practice video to familiarize themselves with the rating procedure. Following this practice trial, the main experiment started. On each trial, participants watched a video and subsequently evaluated it on the dimensions of interest.

All participants viewed the entire set of 36 videos, in random order. During the evaluation phase, participants used a Visual Analog Scale (VAS) ranging from 0 to 100 to rate the videos on valence (from neutral to very negative), arousal (from very calm to very excited), unusualness (from very common to very uncommon), unpredictability (from very predictable to very surprising), and visual complexity (from very simple to very complex). The median duration of the experiment was 35 minutes.

In addition to the evaluation of videos by human observers, we assessed the objective visual complexity of the videos using a new image complexity metric (Rspt) based on detectability suprathreshold (Durmus, 2020). R_{spt} quantifies the number of detectable regions in an image and considers an image with a high number of regions to be more complex. For each video, R_{spt} was calculated for each frame, then the mean and standard deviation of all frames were calculated to measure the average visual complexity of the video and the change in complexity over time, respectively.

Video selection. Based on the ratings obtained in the online study, a total of 16 out of the 36 videos were selected. The selection criteria were: (1) adherence to expected valence; (2) exclusion of videos with high valence variance; and (3) within a valence category (negative vs. neutral), exclusion of videos containing similar events (e.g., two car accidents). In addition, we took care to select negative and neutral videos that were matched in duration (the duration of the selected videos ranged from 12 to 34 seconds), as this is an important determinant of the rate of event compression in memory (Leroy et al., 2024). Although we had initially planned to try to select negative and neutral videos matched on unusualness, unpredictability, and subjective visual complexity, this was not possible as the distribution of negative and neutral video ratings on these dimensions barely overlapped. However, we were able to select negative and neutral videos that were matched in objective visual complexity (both for mean and SD of complexity).

For each video dimension rated in the online study, differences between negative and neutral videos were assessed using a linear mixed-effects model. The model included a dichotomous predictor coding for the type of video (with neutral videos as reference) as fixed effect and the maximal random structure justified by the design: a by-participant random intercept, a by-participant random slope, and a by-item (video) random intercept. The analyses were performed using the robustlmm package in R (Koller, 2016) and the parameters package (Lüdecke et al., 2020) was used to obtain uncertainty intervals (equal-tailed) and *p*-values (two-tailed) using a Wald *t*-distribution approximation.

The mixed-effects analyses confirmed that negative videos were rated as more negative (b = 80.70, SE = 1.95, 95% CI [76.89, 84.52], t = 41.47, p <.001) and more arousing (b = 53.12, SE = 3.29, 95% CI [46.67, 59.57], t = 16.14, p <.001) than neutral videos. In addition, negative videos were also rated more unusual (b = 69.73, SE = 4.37, 95% CI [61.17, 78.28], t = 15.97, p <.001) and less predictable (b = 60.74, SE = 4.08, 95% CI [52.74, 68.73], t = 14.89, p <.001) than neutral videos. The observed differences for these two dimensions are not particularly surprising, as unpredictability and unusualness are known to be associated with emotion (Cahill & McGaugh, 1995).

Subjective visual complexity was also rated higher for negative than neutral videos (b = 15.29, SE = 4.91, 95%CI [5.67, 24.91], t = 3.11, p = 0.002). However, this difference in complexity was not found for the measures of objective visual complexity. For the mean objective complexity, a *t*-test did not show a statistically significant difference between negative and neutral videos ($t(14)$ = 0.62, p = 0.546, d = 0.31, 95% CI [-1.29, 0.69]). Similarly, there was no difference between the two types of videos for the standard deviation of complexity ($t(14)$ = 0.19, p = 0.848, d = 0.10, 95% CI [-0.89, 1.07]). These results align with previous research indicating that emotional stimuli are often perceived as subjectively more complex than neutral stimuli, even when they do not differ in objective complexity (Madan et al., 2018).

Finally, there was no significant difference between the duration of negative and neutral videos ($t(14) = 0.02$, $p = 0.984$, $d = 0.01$, 95% CI [-0.97, 0.99]). This result is critical because studies on temporal compression have shown that video duration significantly influences memory compression rates (Leroy et al., 2024).

Table S1

Databases inspected for the selection of stimuli

Databases	References
Database of Emotional Videos from Ottawa (DEVO)	(Ack Baraly et al., 2020)
The Emotional Movie Database (EMDB)	(Carvalho et al., 2012)
The Chieti Affective Action Videos database (CAAV)	(Di Crosta et al., 2020)
LIRIS-ACCEDE	(Baveye et al., 2013)
E-MOVIE	(Maffei & Angrilli, 2019)
OpenLAV	(Israel et al., 2021)
Real-life news events	(Samide et al., 2020)
MAHNOB-HCI	(Soleymani et al., 2012)
FilmStim	(Schaefer et al., 2010)
Affective Video Database Online Study (ADVOS)	(Gnacek et al., 2022)
AMIGOS	(Miranda-Correa et al., 2021)
Verbal and Non-verbal Contemporary Film Stimuli	(Jenkins & Andrewes, 2012)
Mix film clip library	(Samson et al., 2016)

Supplementary analyses

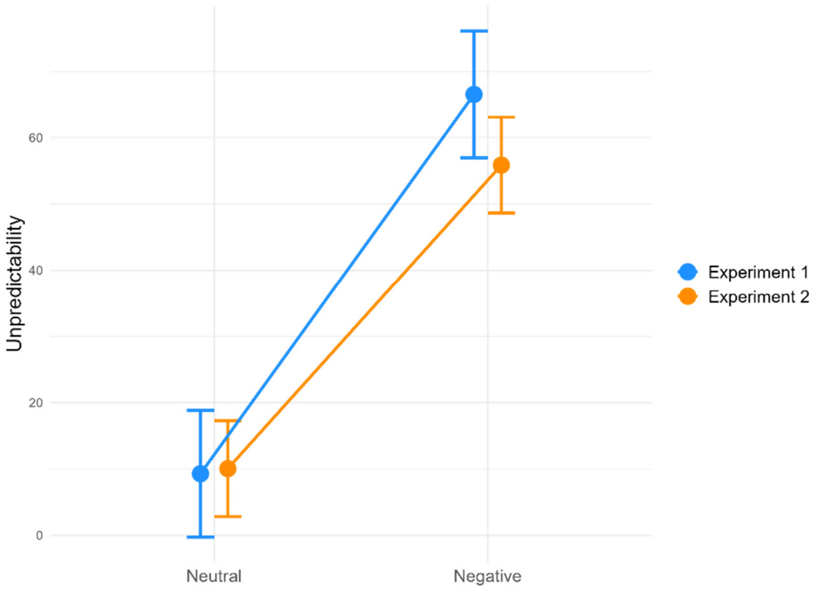
Comparison between Experiments 1 and 2 for the dimensions of unpredictability and unusualness

We also examined whether the stronger effect of negative emotion on memory measures in Experiment 2 compared to Experiment 1 could be due to differences in the perceived unpredictability and unusualness of the stimuli. To examine this possibility, we compared ratings for these two dimensions between Experiments 1 and 2. For each dimension, we fitted a robust mixed-effects model with the type of video, experiment, and their interaction as predictors. For unusualness, we found a main effect of the type of video (b = 72.53, SE = 4.71, 95% CI [63.29, 81.78], t = 15.39, p < .001), but there was no main effect of experiment (b = 2.03, SE = 2.58, 95% CI [-3.04, 7.10], t = 0.79, p = 0.432) and no interaction between the type of video and experiment (b = -5.30, SE = 3.85, 95% CI [-12.86, 2.26], t = 1.38, p = 0.169).

For unpredictability, we found a main effect of the type of video (b = 51.53, SE = 5.52, 95% CI [40.70, 62.35], t = 9.34, p < .001), no main effect of experiment (b = -4.94, SE = 2.63, 95% CI [-10.11, 0.23], t =-1.88, p = 0.06), and a significant interaction between the type of video and experiment (b = -11.41, SE = 3.26, 95% CI [-17.81, -5.02], t =-3.50, p < .001). This interaction indicated that the difference in unpredictability between negative and neutral videos was slightly bigger in Experiment 1 than Experiment 2 (see Figure S1). However, this cannot easily account for our finding that the effect of negative emotion on memory measures was larger in Experiment 2 than Experiment 1 (if unpredictability played a role, the reverse effect should have been observed).

Figure S1

Interaction between type of video and experiment for unpredictability



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