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Event segmentation reveals working memory forgetting rate

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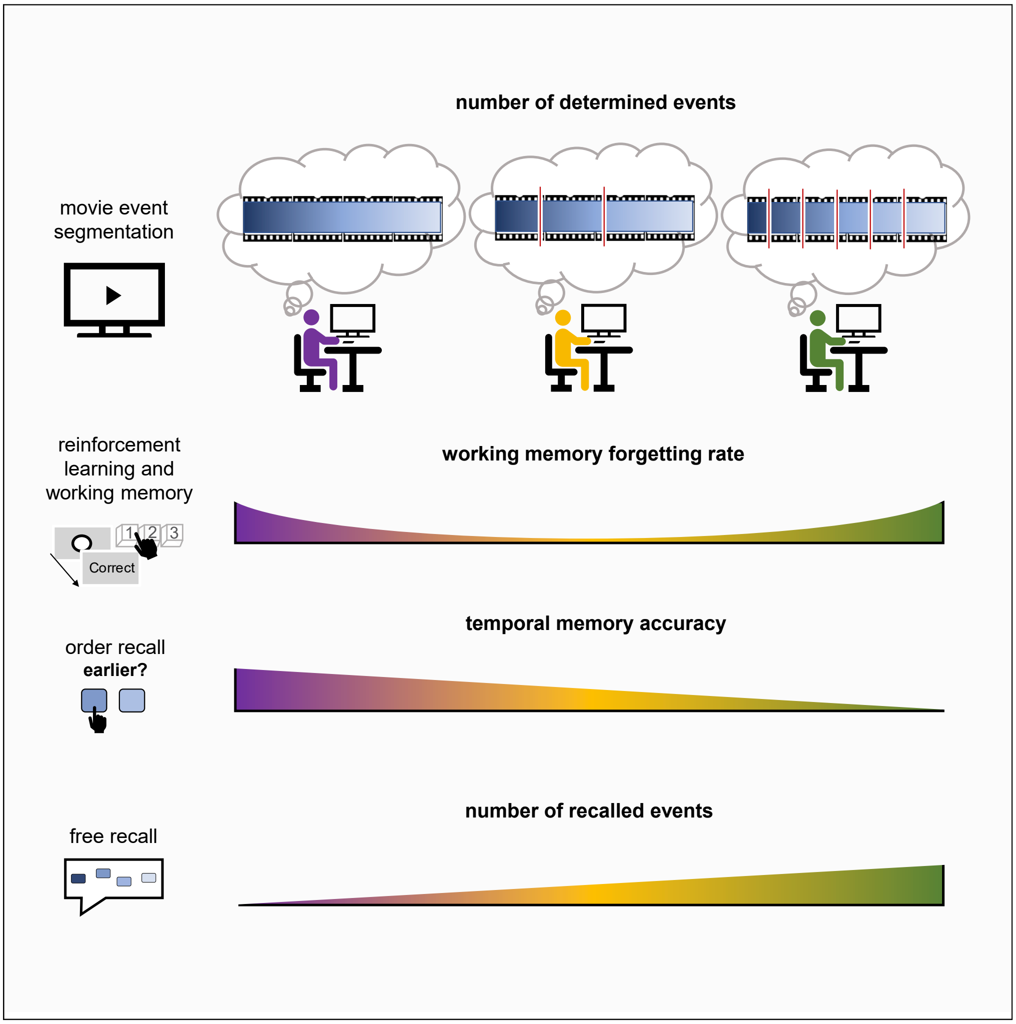

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Highlights

The event segmentation grain is variable across individuals

The event segmentation grain has a U-shaped relationship with the WM forgetting rate

The temporal order memory accuracy decreases with the increasing event segmentation

The number of recalled events increases with the increasing event segmentation

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Event segmentation reveals working memory forgetting rate

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SUMMARY

We encounter the world as a continuous flow and effortlessly segment sequences of events into episodes. This process of event segmentation engages working memory (WM) for tracking the flow of events and impacts subsequent memory accuracy. WM is limited in how much information (i.e., WM capacity) and for how long the information is retained (i.e., forgetting rate). In this study, across multiple tasks, we estimated participants' WM capacity and forgetting rate in a dynamic context and evaluated their relationship to event segmentation. A U-shaped relationship across tasks shows that individuals who segmented the movie more finely or coarsely than the average have a faster WM forgetting rate. A separate task assessing long-term memory retrieval revealed that the coarse-segmenters have better recognition of temporal order of events compared to the fine-segmenters. These findings show that event segmentation employs dissociable memory strategies and correlates with how long information is retained in WM

INTRODUCTION

Event segmentation is the process of discretizing a flow of events into episodes (Zacks et al., 2007; Zacks and Swallow, 2007). It is done naturally even without instructions (Jafarpour et al., 2019). Event segmentation is thought to be fundamental in shaping cognitive processes such as working memory (Kurby and Zacks, 2008; Radvansky, 2017; Richmond et al., 2017). Current event segmentation models posit that working memory tracks the flow of events to determine the segments, and within an event segment WM integrates information and retains 'what is happening now' (called event models; Kurby and Zacks, 2008; Sargent et al., 2013). An event segment is thought to end when a perceived event does not match the expectations of what would proceed from a prior flow of information (Bein et al., 2020; Franklin et al., 2020). However, working memory limitations may contribute to event segmentation. A working memory system that fails to retain information must update the event model often or utilize other strategies to compensate for its limitations. It is known that people who segment the flow of events in a standard way, that is, as defined by the experimenter, have better working memory performance than those with a discrepancy in event segmentation (Karuza et al., 2019; Sargent et al., 2013).

It is not clear what aspect of working memory is linked to event segmentation. Here, we examined the link between the number of segmented events and working memory limitations. We focused on two independent aspects of working memory: the amount of information retained and the duration of maintenance (Baddeley, 2012, 2003; Bays and Husain, 2008; D'Esposito and Postle, 2015; Oberauer et al., 2018). The first factor, how much information can be held in memory, defines working memory capacity (Bays et al., 2009; Burgess and Hitch, 1992; Cowan, 2010; Vogel and Machizawa, 2004). The other factor, how long the information persists in the face of time and interference, is measured as the working memory forgetting rate (Baddeley, 2012; Collins and Frank, 2012). A challenge in quantifying these limitations is that other memory systems, such as long-term memory, can also contribute to the accuracy of working memory (Jafarpour et al., 2017; Rose et al., 2016; Zokaei et al., 2014). In this study, we implemented a working memory association learning task, designed by Collins and Frank (2012), which disentangles working memory from other forms of learning including episodic memory. The task requires learning associations between images and actions in blocks of variable image set sizes (Figures 1B and 1C). The task allowed us to computationally estimate the working memory capacity and forgetting rate in each participant. We modeled the association learning behavior with a dynamic mixture of learning and working memory components (adapted from Collins et al. (2017)). This reinforcement learning and working memory (RLWM) model and the task

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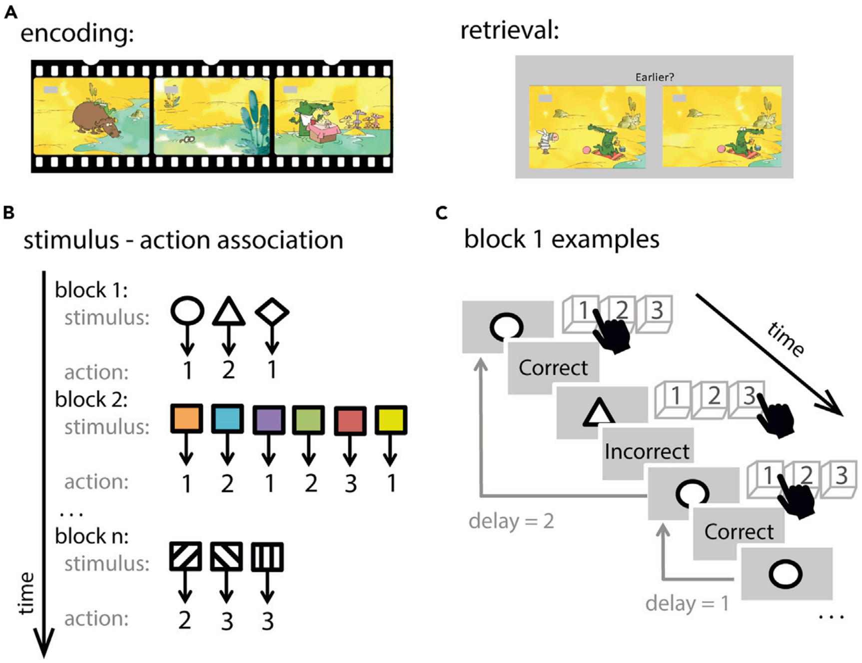

Figure 1. Experimental design: The experiment consisted of four parts, the first two of which are depicted here

(A) Temporal memory test: At encoding (left), participants watched two muted movies (three frames from one movie is shown). At retrieval (right), participants saw two movie frames and determined their temporal order by pressing the left or right key. There were 35 temporal order questions per movie.

(B) Association learning task: Participants performed a block-design association learning task. In each block, participants learned the association between a set of images and actions by trial and error. There were three possible actions (key 1, 2, or 3) and feedback was provided. The image set size varied across blocks, ranging from 2 to 6.

(C) Three example trials. 'Delay' parameter quantifies the number of intervening trials from the last time the stimulus was encountered. The last two parts of the experiment were segmentation and free recall tasks

characterize working memory used in dynamic contexts that involve multiple memory systems. For that reason, we considered it to be suitable for relating to potential working memory use in dynamic naturalistic experiments where multiple memory systems may also be engaged, such as naturalistic event segmentation.

The RLWM model parameterizes working memory limitations as the probability that the stimulus-action association can be kept in working memory and can be used accurately for choosing the rewarded associated action in the future. The association learning task manipulates working memory limitation with discrete set sizes and delays; hence, the model approximates the working memory resource limitation to the number of retained associations, akin to the slot model, ranging from 2 to 6 (Cowan, 2000; Ma et al., 2014). Accordingly, the probability that the correct stimulus-action association is available in working memory depends on the working memory capacity C and set size ns. Specifically, if the set size is within capacity, the model makes maximal use of information in WM, but if the set size is larger, information in WM contributes less to choices. Items are stored in WM according to the probability $\frac{C}{n_s}$. The working memory forgetting rate in RLWM approximates how fast the memory of the retained association is forgotten when facing new stimuli. The WM forgetting rate indicates how fast the probability of selecting a correct association decayed to the chance level ($\frac{1}{n_a}$, where $n_a = 3$ is the number of possible actions).

Traditionally, event segmentation has been studied with experimentally designed boundaries, where a change in an associated stimulus, such as the background image or the semantic category of a sequence of images, determines a new segment (DuBrow and Davachi, 2013; Ezzyat and Davachi, 2014), or in a naturalistic stream of events the expected event boundaries are defined by the experimenter (Sargent et al., 2013; Speer et al., 2003, 2007). In these cases, event segmentation is discussed as the agreeability of an individual's segmentation with the predefined event boundaries. The empirical data, however, show that the segmentation of a naturalistic sequence of events is more subjective. Although event segmentation can be modulated to a fine or coarse grain through instructions (Sargent et al., 2013; Speer et al., 2007), across a population, individuals differ in how many events they identify (Jafarpour et al., 2019; Sargent et al., 2013; Zacks et al., 2006). For example, the maximum agreeability in event segmentation in Speer et al. (2003) was at 80% (n = 11) and in Jafarpour et al. (2019) was at 60% (n = 80). Here, we investigated the source of individual variability in event segmentation without assuming predefined event boundaries.

We hypothesized that subcomponents of memory are linked to the number of identified boundaries in a flow of events (i.e., the number of events). One possibility is that infrequent segmentation overwhelms working memory storage, resulting in faster forgetting and poor subsequent memory of events. Another possibility is that limited working memory constrains information retention leading to frequent segmentation and utilization of other memory systems such as long-term memory. It is evident that event segmentation impacts episodic memory (DuBrow and Davachi, 2013, 2014; Ezzyat and Davachi, 2011, 2014; Tubridy and Davachi, 2011), event boundaries are more memorable than other events, and remembering the temporal order of events across event boundaries is more difficult than within the event segments (Heusser et al., 2018; Horner et al., 2016). We predicted that frequent event segmentation would enhance long-term memory and diminish temporal order memory.

We studied the relationship between event segmentation and working memory by administering two independent tasks (a movie segmentation task and a working memory/association learning task) to healthy participants (part 1 of data collection was conducted in the lab and part 2 was conducted online because of COVID-19 mitigation plans; Figure 1). Participants watched a movie and were subsequently tested on their memory. They later watched the same movie and reported subjective event boundaries. We allowed the individual to utilize their natural strategy for event segmentation. All movies were novel (sound off) animations with simple illustrations (Figure 1). We selected movies with different storylines: the storyline of one of the movies was nonlinear so that interchanging the epochs of the movie did not affect the story, the other movie had a linear storyline with noninterchangeable epochs (see STAR Methods for the storylines). Including both linear and nonlinear storylines allowed us to observe whether individual variability in event segmentation is because of utilizing stories, such as schematic knowledge of the story (Bower et al., 1979), or whether segmentation variability is independent of story knowledge (Sargent et al., 2013). The study also included the association learning task with variable association set sizes (Collins et al., 2017). We used the described RLWM model to estimate the participant's WM capacity and forgetting rate. Finally, participants performed a temporal order recognition task and wrote a paragraph about the movies, i.e., a free recall task.

RESULTS

Number of determined event boundaries has a U-shaped relationship with the WM forgetting rate

Behavioral results for individual tasks were consistent with previous studies. In particular, we replicated the established observation that RLWM provided the best fit compared to reinforcement learning (RL) models without a working memory component (Figure S1). We focus here on cross-task results. The cross-task comparison showed a U-shaped relationship between the variation in the total number of determined events in the movies and the working memory forgetting rate (mixed-effect Quadratic $F(1,56) = 5.7$, $p = 0.02$; linear component $F(1,56) = 2.73$, $p = 0.1$, where F-statistical value is defined as Mean Square divided by mean squared error; Figure 2A), but there was no linear or quadratic relationship between working memory capacity and the number of events (mean capacity = 3.38 (SD = 1.10); mixed-effect linear fit $p = 0.45$; quadratic fit $p = 0.42$).

Separately studying the data collected in the lab (part 1, n = 32) and online (part 2, n = 27), we observed the U-shaped relationship in the part 1 (Quadratic $F(1,29) = 12.9$, $p = 0.001$; linear fit $F(1,29) = 0.085$, $p = 0.77$), and the right tail of the U-shaped in part 2 (Quadratic $F(1,24) = 0.16$, $p = 0.68$; linear $F(1,24) = 5.3$, $p = 0.029$; Figure 2A). The online data collection yielded a finer segmentation ($t(57) = -4.27$, $p < 0.001$; across the participants, the total number of determined events was between 2 and 73 events; M = 29.13, SD = 18.12). Nevertheless, in both part 1 and part 2, the number of events for the two movies correlated (Spearman $r = 0.85$, $p < 0.001$; part 1: $r = 0.86$, $p < 0.001$; part 2: $r = 0.77$, $p < 0.001$). Therefore, subjective segmentation strategy occurred irrespective of the movie's storyline.

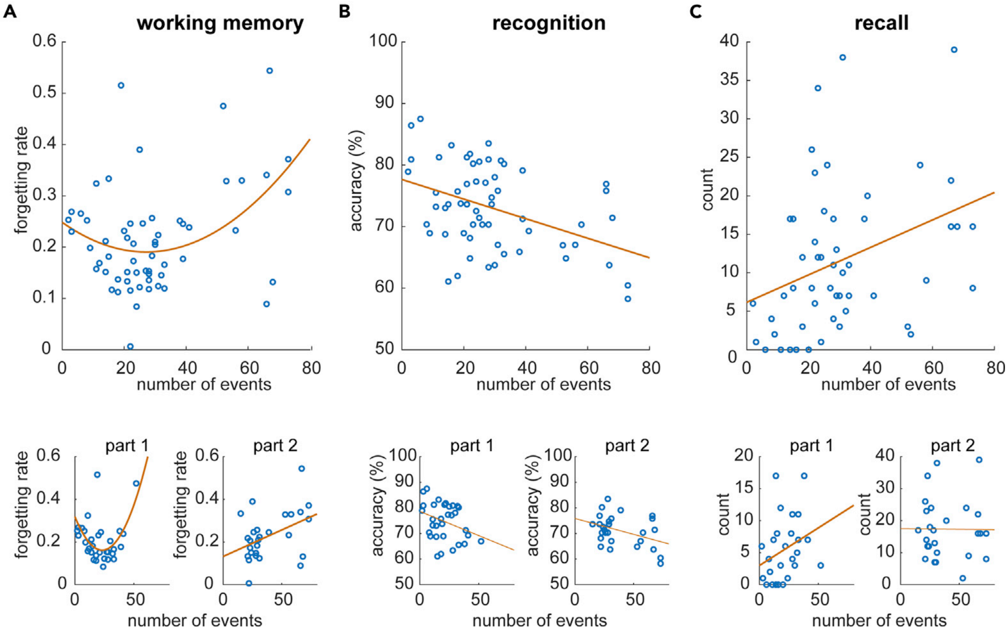

Figure 2. Cross-task results

(A) The total number of determined events and working memory forgetting rate had a U-shaped relationship. Top plots show all data and bottom plots show data separately for part 1 and part 2 of data collection.

(B) The temporal order recognition accuracy decreased with the increasing number of determined events.

(C) The number of realis (factual verbs) at recall increased with segmentation. Each dot depicts a participant. The thicker curves denote significant relationships ($p < 0.05$).

The accuracy in temporal order memory decreases but the number of recalled events increases with the increasing number of determined event boundaries

We also observed that the temporal order recognition correlated with segmentation performance, so that with fine segmentation, the temporal memory was disturbed (Spearman ranked $r = -0.33$, $p = 0.008$; mixed-effect model $F(1,57) = 12.59$, $p < 0.001$; Figure 2B; part 1: $r = -0.27$, $p = 0.12$; part 2: $r = -0.31$; $p = 0.10$). There was no presumed number of events in the movies of this experiment to subsequently count the number of recalled events; instead, we used natural language processing measurements for counting the recall length and number of factual ''realis'' events (Sap et al., 2020; Sims et al., 2019). We did not observe any false memories or intrusions in the movie summaries, and we observed a relationship between event segmentation and number of realis events (Spearman $r = 0.38$, $p = 0.004$; mixed-effect $F(1,51) = 0.46$, $p = 0.49$; part 1: $r = 0.37$, $p = 0.06$; part 2: $r = -0.09$, $p = 0.64$; Figure 2C) but not the recall length overall ($r = 0.068$, $p = 0.62$; part 1: $r = 0.34$, $p = 0.08$; part 2: $r = -0.15$, $p = 0.43$).

In this study, part of the data was collected online because of the COVID-19 pandemic mitigation plan. The online data collection was not conducted in a controlled environment and the long study was not optimal for an online platform. To be consistent with the in lab experimental data, we excluded participants from online data collection who performed poorly in comparison to the in-lab data collection, at any part of the experiment to ensure that all the included participants were fully engaged (see the STAR Methods and Figure S2 for details). We did not have any theoretical limitation on what an acceptable range of event segmentation or recall length would be; therefore, similar to the part 1, in part 2 we only excluded the outliers in segmentation and recall.

DISCUSSION

We observed a relationship between event segmentation, working memory forgetting rate, and subsequent memory performance. We used a newly-established task measuring the use of working memory in a dynamic decision-making context (Collins and Frank, 2012) to estimate the participants' working memory capacity and forgetting rate. Using cross-task comparisons, we found that participants who segmented the movies into either fine or coarse segments compared to the average segmentation have a faster working memory forgetting rate, as detected with a U-shaped relationship between segmentation and WM forgetting rate. Previously, Sargent et al., (2013) showed that event segmentation correlates with working memory performance in reading span, operation span, and word-list memory tasks (Daneman and Carpenter, 1980; Turner and Engle, 1989). In that study, event segmentation was assessed as the discrepancy from a normative experimentally assumed event boundary. In that case, the fine and coarse segmentation would have been characterized with a low segmentation ability and poor working memory. The adopted working memory tests in the previous study, however, could not clarify what aspect of working memory limitation is linked to event segmentation. In this study, we found a relationship between event segmentation and working memory forgetting rate. These findings suggest that event segmentation is related to the retention of the flow of events, rather than the retention of information which would be limited by working memory capacity.

At encoding, perception of event boundaries naturally engages the memory network (Jafarpour et al., 2019) and increases recall performance (Newtson and Engquist, 1976; Pettijohn et al., 2016; Sols et al., 2017). Furthermore, people remember the event-boundaries better than other events (Newtson and Engquist, 1976). It has previously been shown that a fine-grained segmentation strategy benefits source memory (Hanson and Hirst, 1989, 1991; Heusser et al., 2018). Consistent with these findings, we also observed a higher number of realis events in narrated recall. However, with fine segmentation, the contextual representation of a sequence is updated resulting in reduced access to the temporal memory of events that occurred across event boundaries, i.e., ''walking through doorways'' effect (DuBrow and Davachi, 2014; Pettijohn and Radvansky, 2016). Congruent with this previous work, we observed that temporal order recognition accuracy decreased with fine segmentation.

Computational models of event segmentation suggest that sequences are segmented based on predictions from prior knowledge about sequences of events, perhaps by utilizing stories (Hsieh et al., 2014; Schapiro et al., 2013; Zacks et al., 2011), or the sequences of events are linked to a temporal context that changes with event boundaries (DuBrow and Davachi, 2014; Franklin et al., 2020; Howard et al., 2005; Lositsky et al., 2016; Radvansky and Zacks, 2011; Zacks and Swallow, 2007). Indeed, a change in the story or temporal context with segmentation leads to less accessibility of memory of temporal order of events across boundaries, and retaining the temporal context benefits temporal memory (DuBrow and Davachi, 2014; Horner et al., 2016; Manning et al., 2011). Here, we showed that working memory forgetting rate also plays a role in event segmentation. In a naturalistic setting, retention can be attained by utilizing long-term memory or relying on a working memory system with a slow forgetting rate.

An outstanding question concerns the causality of the relationship between working memory and event segmentation. One possibility is that working memory is a primary cognitive mechanism and event segmentation is determined by limits in working memory. Accordingly, participants with faster forgetting rates use alternative mechanisms such as utilizing scripts or long-term memory to compensate (Keidel et al., 2017). An alternative possibility is that event segmentation is a primary cognitive mechanism (Ongchoco and Scholl, 2019; Radvansky, 2017; Richmond et al., 2017). In this case, participants who segment more often lose access to the information from the previous events (Ezzyat and Davachi, 2014; Horner et al., 2016) leading to a fast forgetting rate or to relying on storylines to keep a track of what happened. A third possibility is that both working memory and event segmentation engage common cognitive mechanisms, such as utilizing stories or scripts, as utilizing a script facilitates memory (Farag et al., 2010; Gobet et al., 2015; Sargent et al., 2013; Zacks et al., 2010). For example, a phone number's schema enables effective segmentation and memory for a 10-digit number (Miller, 1956).

In conclusion, we observed that the working memory forgetting rate reflects individual differences in event segmentation. A relationship between the number of determined events on one task and the forgetting rate on another task suggested that participants with a faster forgetting rate used two different strategies during encoding and retrieval that differentially affected temporal order recognition. Taken together, these data suggest that working memory plays a key role in shaping event segmentation, and people with faster working memory forgetting rates utilize alternative cognitive processes for encoding and retrieval of events.

Limitations of the study

The observed individual variability cannot be explained by the participants' level of task engagement. Individuals who identified fewer events potentially a less motivated group (coarse segmenters) performed better in the memory recognition test. In addition, all participants' memory and learning performances were above chance. Nevertheless, additional studies will be needed to determine the scope of the relationship between individual difference in event segmentation and utilizing stories or free recall. For example, it would be noteworthy to study whether the observed link between segmentation and temporal order memory generalizes to other behavior such as generating stories and imagination.

STAR★METHODS

Detailed methods are provided in the online version of this paper and include the following:

- KEY RESOURCES TABLE
- RESOURCE AVAILABILITY
  - Lead contact
  - Materials availability
  - Data and code availability
- EXPERIMENTAL MODEL AND SUBJECT DETAILS
- METHOD DETAILS
- QUANTIFICATION AND STATISTICAL ANALYSIS
  - Association learning
  - Movie segmentation
  - Modeling
  - Two-parameters reinforcement learning (RL2)
  - Four-parameters reinforcement learning (RL4)
  - Reinforcement learning and working memory (RLWM)
  - Cross-task comparison
  - Learning and working memory results without RLWM
- MOVIES STORIES
  - Non-linear storyline
  - Linear storyline

SUPPLEMENTAL INFORMATION

Supplemental information can be found online at https://doi.org/10.1016/j.isci.2022.103902.

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AUTHOR CONTRIBUTIONS

Conceptualization Ideas, A.J.; Methodology, A.J.; Software, A.J. and A.G.E.C.; Validation, A.J. and A.G.E.C.; Formal Analysis, A.J. and A.G.E.C.; Investigation, A.J.; Writing – Original Draft, A.J.; Writing – Review & Editing, A.J., E.A.B., R.T.K., and A.G.E.C.; Visualization, A.J.; Supervision, E.A.B., R.T.K., and A.G.E.C.; Funding Acquisition, A.J., E.A.B., and R.T.K.

DECLARATION OF INTERESTS

The authors declare no competing interests.

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STAR★METHODS

KEY RESOURCES TABLE

REAGENT or RESOURCE	SOURCE	IDENTIFIER
Deposited data		
cross-task data	OSF.io	https://doi.org/10.17605/OSF.IO/XV4Z9
Software and algorithms		
Script	github.com	https://github.com/annaja/iScience2022
MATLAB	Mathworks	https://www.mathworks.com/products/matlab.html
jsPsych	jsPsych.org	https://www.jspsych.org/

RESOURCE AVAILABILITY

Lead contact

Further information and requests for resources and reagents should be directed to and will be fulfilled by the lead contact, Anna Jafarpour (annaja@uw.edu).

Materials availability

This study did not generate new unique reagents.

Data and code availability

The data and the analysis code have been deposited and are publicly available at https://github.com/annaja/iScience2022. Any additional information required to reanalyze the data reported in this paper is available from the lead contact upon request.

EXPERIMENTAL MODEL AND SUBJECT DETAILS

Part 1: 36 healthy and English-speaking adults (25 female) were recruited through the online University of Berkeley Psychology Department Research Participation Program. Participants provided informed consent and were compensated ($36 or 3 course-credits). The Office for the Protection of Human Subjects of the University of California, Berkeley approved the study protocol. The mean age was 20.3 (SD = 1.9) and ranged from 18 to 27. 29 of 36 participants performed the additional free-recall task (the data from the first 7 participants was not recorded due to a technical issue). All participants were right-handed by self-report. We discarded one participant because she identified two standard deviations more events than the group average but including her did not change the results. The minimum temporal order recognition accuracy for the linear movie was at 66% and for the non-linear movie was at 54%. RLWM did not accurately model the performance of three participants. The estimated learning rate was too high ($\alpha > 0.9$, two standard deviations larger than the mean; M = 0.16, SD = 0.33) and the estimated mixture weight was too low ($w_0 < 0.6$; M = 0.83, SD = 0.18) in the three participants, indicating that the working memory module of the model was not functioning in a regime representative of cognitive working memory function.

Part 2: 101 healthy and English-speaking adults were recruited through the online University of Berkeley Psychology Department Research Participation Program. They provided an informed consent and received course credits for the participation. The study was run remotely by providing a link to the online task. Participant's ran the study at their desired time of the day. 98% of participants performed above 70% for the last trials of learning trials for set size 2 (Figure S2). 50% of participants wrote something about the movies. 65.3% of participants performed the order of events in the linear (easier) movie for at least as well as the worst participant performance in experiment 1 (at 66%; although theoretically, 50% accuracy would be the chance level, without experimenter's supervision, we could not assure that lower performance than an in-lab result (experiment 1) would be from an active participation).

We did not have a theoretical limitation on how many events are in the movies, therefore, we only excluded the outliers. In part 2, 19 participants did not indicate any events in the movie and two participants were excluded for outlier number of events. Accordingly, 76% of participants had acceptable number of events. Cross-tasks, 27 of participants fulfilled all tasks. There were 19 female (8 male), age ranged from 18 to 22 (two participants did not report their age, mean = 20 years, SD = 1.2). Together with in lab data collection, we reported the results based on 59 subjects.

METHOD DETAILS

Part 1: The experiment ran on a desktop PC and a standard TFT monitor, in a sound-attenuated recording room. It consisted of four parts. First, participants watched two novel mute animations (each ~3 min long) with differing storylines linear (interchanging the movie epochs hurts the story), and non-linear (interchanging the movie epochs did not hurt the story, like Tom and Jerry animation). They were instructed to watch the movies carefully because we would ask questions about them. The types of storylines were identified by asking a group of naïve observers about the interchangeability of epochs of the movies.

There were 35 recognition memory tests per movie. At each test, subjects saw two scenes from a movie - located on the left and right sides of the screen for 2 s. Then a prompt appeared asking the participant to indicate the order of the scenes. Half of the prompts were asked which scene was 'earlier' or others asked which scene was 'later', in a pseudo-random trial order (Figure 1). Participants used left or right arrow keys to respond. The tested movie scenes were between 1.6 to 62 s for the non-linear movie (M = 16.66, SD = 17.27) and 1.6 to 48 s for the linear movie (M = 15.02, SD = 13.22).

The participant then performed a version of an association learning task (Figures 1B and 1C) to evaluate working memory characteristics, namely working memory capacity and forgetting rate (Collins et al., 2017). In this task, participants used their dominant hand to select from three possible actions when they saw an image. The possible actions were pressing the J, K, and L keys from a keyboard (depicted as action 1, 2, and 3 in Figure 1). They used trial and error to learn the correct image-action association. The probability of an action being paired with an image was equal (1/3); thus, an action could pair with more than one stimulus. Participants learned the associations in 12 repetitions of each stimulus; the repetitions were pseudo-randomly interleaved. This procedure repeated in a block-design and included 22 blocks (3 blocks of set sizes 6, 5, and 4; 4 blocks of set size 3, and 6 blocks of set size 2). The stimulus set-size varied in each block to manipulate the requirement for capacity-limited and delay-sensitive working memory (Figure 1C). Participants studied the whole stimuli set at the beginning of each block.

The reward value for a correct response differed across stimuli; an incorrect response yielded no reward. Only one action for a stimulus was correct and each correct stimulus-action association was assigned a probability (p) of yielding a 2-point versus a 1-point reward, and this probability was either high (p = 0.80), medium (p = 0.50), or low (p = 0.20). We counter-balanced the probability within-participant and blocks to ensure an equal overall value of different set sizes and actions. Participants had 1.4 s to respond. The feedback was displayed for 0.5 s. There was an inter-stimulus interval of 0.5–0.8 s in which a fixation cross was shown.

After performing the association learning task, participants watched the movies again; this time they segmented the movies by pressing a spacebar to indicate the start of a new event. We instructed them to press a key "whenever something new happened." We told the participants: "we want to segment this movie into episodes", and we explained that segmentation could occur as often as they liked. The consistency of frequency of event segmentation for each participant was determined across the three movies. Finally, participants performed a surprise free recall test, where they were asked to write a paragraph describing the story of each movie. Participants were instructed not to worry about grammar and wording - simply "write what came to their mind." The free recall test allowed us to investigate the relationship between the individual difference in event segmentation and subsequent memory performance.

Part 2: We collected more data online. Participants remotely ran the study on their personal computers. The study was written in javascript using jsPsych (de Leeuw, 2015). It included the association learning task, the encoding of the linear and non-linear movies, the recognition of temporal order of the movies, followed by the event segmentation task and free recall.

QUANTIFICATION AND STATISTICAL ANALYSIS

Association learning

We analyzed the association learning task in two ways, without modeling and with reinforcement learning and working memory (RLWM) modeling, consistent with previously published studies (Collins, 2018; Collins et al., 2014, 2017; Collins and Frank, 2018). Trials with missed responses or with less than 200 ms response time were discarded. To generate learning curves, we analyzed the proportion of correct choices as a function of the number of iterations (how many times the stimulus was encountered) and set size. Next, we used a multinomial logistic regression to evaluate the performance with respect to three parameters - the set size (number of stimuli in a block), delay (number of trials since the last correct choice for the current stimulus), and previously correct answers (number of correct choices made so far for the current stimulus) - and their interactions. We quantified the effect of working memory and learning on a trial-by-trial basis by modeling the probability of a correct choice for each participant as a function of the three parameters: set size, the number of previously correct answers, and delay (see Collins et al. (2017) for details).

Movie segmentation

We evaluated the keypresses during the movies and discarded any keypress that occurred less than 100 ms from the previous keypress to remove multi-clicks. Then we quantified the number of events by counting key presses for each movie. A ranked (Spearman) correlation was utilized to identify the consistency of individual differences across the movies.

Modeling

We fit three models to the trial-by-trial responses for each subject: two-parameters reinforcement learning (RL2), four-parameters reinforcement learning (RL4), and a modified RLWM model (Collins et al., 2017). We used the Akaike Information Criterion (AIC) to select the best model considering the number of parameters used in each model. RLWM was used as a baseline. A model's relative AIC was quantified by subtracting the model's AIC by RLWM's AIC and dividing the answer by RLWM's AIC. We also simulated data based on the models for validation.

Two-parameters reinforcement learning (RL2)

The basic model was a reinforcement learning model (without the working memory component) with a delta rule learning. For each stimulus, s, and action, a, the expected reward was $Q(s,a)$, and the Q value was updated with observing feedback, r_t, through time. The Q values were updated based on a learning rate, α, and the difference between expected and observed reward at trial t (known as the prediction error: $\delta_t = r_t - Q_t(s,a)$): $Q_{t+1}(s,a) = Q_t(s,a) + \alpha \times \delta_t$. Choosing an action utilized the expected reward value. An action was probabilistically chosen, with a greater likelihood of selecting an action that had a higher Q value, using the SoftMax choice rule: $P(a|s) = e^{\beta Q(s,a)}/\sum_i(e^{\beta Q(s,a_i)})$, where β is an inverse temperature free parameter. This model had two parameters of α and β.

Four-parameters reinforcement learning (RL4)

This model in addition to RL2 includes a value for unrewarded correct responses and undirected noise in action selection. In this experiment, a correct response was sometimes rewarded and sometimes not rewarded. We estimated how much a person valued a correct response, irrespective of the reward by estimating the value for correct-but-not-rewarded items, i.e., r_0. The model also considered an undirected noise, $0<\varepsilon<1$, in the stochastic action selection, to allow for choosing an action that did not have the highest Q value. Accordingly, $P \leftarrow (1-\varepsilon) \times P + \varepsilon \times \frac{1}{n_a}$, where $1/n_a$ is a uniform probability of choosing an action.

Reinforcement learning and working memory (RLWM)

We applied RLWM to estimate the working memory capacity and forgetting rate of the participants (Collins et al., 2017). This model had 8 parameters and consisted of two components. A working memory component with limited working memory *capacity, C*, and *forgetting rate*, $\varnothing_{WM}$. The Q value was subject to decay with a forgetting rate, $0<\varphi<1$, so for all the stimuli that are not current, $Q \leftarrow Q + \varphi(Q_0 - Q)$, where $Q_0 = \frac{1}{n_s}$.

The RL component had a *learning rate*, α, value for an unrewarded correct response, r_0, undirected noise, ε, and a *forgetting rate*, $\varnothing_{RL}$ (β was set constant at 100). We also allowed for the potential lack of an impact of negative feedback ($\delta<0$) by estimating a preservation parameter, *pers*. In that case, the learning rate is reduced by $\alpha \leftarrow (1 - pers) \times \alpha$. Accordingly, *pers* near 1 indicated lack of an impact of negative feedback (learning rate close to 0; high preservation of Q value), and *pers* close to 0 indicated equal learning rate for positive and negative feedback.

The WM component was simulated as encoding of stimulus in a Q learning system, like the RL component but the outcome, r_t, was 1 for correct, 0 for incorrect (rather than the observed reward), the learning rate was set to 1 ($\alpha = 1$), and at most C stimuli could be remembered. We formulated the probability of a stimulus being in working memory as:

$$\text{If } r_t = 1, P_{WM}(r_t|s_t,a_t) = \min\left(1,\frac{C}{n_s}\right) \times Q_{wm}(s_t,\ a_t) + \left(1-\min\left(1,\frac{C}{n_s}\right)\right) \times 1\Big/n_a,$$

$$\text{If } r_t = 0, P_{WM}(r_t|s_t,a_t) = \min\left(1,\frac{C}{n_s}\right) \times (1-Q_{wm}(s_t,\ a_t)) + \left(1-\min\left(1,\frac{C}{n_s}\right)\right) \times 1\Big/n_a$$

where $n_a = 3$ is the number of possible actions. In the RL case,

if $r_t > 0$, $P_{RL}(r_t|s_t,a_t) = Q_{RL}(s_t,\ a_t)$

if $r_t = 0$, $P_{RL}(r_t|s_t,a_t) = 1 - Q_{RL}(s_t,\ a_t)$.

A *mixture weight*, w_0, formulated how much each of the components was used for action selection. The weight was $w_0 \times \min\left(1,\frac{C}{n_s}\right)$ to represent the confidence in WM efficiency. This initialization reflects that a participant is more likely to utilize WM when the stimulus set size is low. The overall policy was:

$$P(a|s) = w_t(s) \times P_{WM}(a|s) + (1 - w_t(s)) \times P_{RL}(a|s)$$

A Bayesian model averaging scheme inferred the relative reliability of WM compared with the RL system over time, t:

$$w_{t+1}(s) = \frac{P_{WM}(r_t|s_t,a_t)\ w_t(s)}{P_{WM}(r_t|s_t,a_t)\ w_t(s) + P_{RL}(r_t|s_t,a_t)\ (1 - w_t(s))}$$

, where P_{WM} is the probability that action a is selected for stimulus s according to the WM component at time t and P_{RL} is the probability of action selection according to the RL component. We assumed that although the w_0 is the same for all stimuli, the development of mixture weight over time would be different for each stimulus because the probability of retaining a stimulus in working memory or another retention system is not equal.

Cross-task comparison

We determined a relationship between the number of events and working memory capacity and forgetting rate that were estimated by the RLWM model using a mixed-effect linear and quadratic model fitting, including the dataset (part 1 or part 2) as a random factor which allows the intercept to be different across the datasets (formulated as y ~ x^2 + (1|set), where x is the total number of determined events and y is the WM forgetting rate). We also studied a link between event segmentation and the subsequent memory performance (recall and temporal order memory). We accessed recall by applying natural language processing algorithms to count the number of "realis" events (i.e., factual and non-hypothetical words) and the total number of written words in the free recall task (Sap et al., 2020; Sims et al., 2019).

Learning and working memory results without RLWM

The results of association learning without reinforcement learning modeling also showed a link between working memory limitation and event segmentation. Overall, participants learned the stimulus-action associations. For all set sizes, the accuracy of the last two iterations was on average more than 90% (M = 93.5%, SD = 3%; Figure S1); however, the accuracy decreased with increasing set size ($r = -0.94$, $p = 0.018$). We analyzed the trial-by-trial performance with respect both to set size and to the maintenance of correct associations across intervening trials of a stimulus. The result of a multinomial logistic regression revealed that performance was reduced with increasing set size ($t = -10.12$, $p < 0.001$) and delay (the number of trials since a correct response to the current stimulus ($t = -8$, $p < 0.001$). By contrast, the performance improved with increasing total number of previously correct responses to the current stimulus ($t = 5.95$, $p < 0.001$). The interactions between set size and delay ($t = -8.29$, $p < 0.001$), set size and previous correct responses ($t = 4.19$, $p < 0.001$), and delay and previous correct responses ($t = 5.18$, $p < 0.001$) also affected the performance (Figure S1B), consistent with the previous report (Collins et al., 2017).

MOVIES STORIES

Non-linear storyline

The animation is a sequence of independent events that involve crocodiles. It starts by showing two zebras listening to music next to a swamp. A crocodile suddenly eats one of them. Then, the crocodiles swim in a swamp just below the surface with only the eye visible. One of the crocodiles is wearing glasses. This crocodile stands up for a moment to clean its glasses and then it continues swimming below the surface. Next, a crocodile attacks a cow that is drinking water. The cow is too big for the crocodile so it cannot bite it. The cow, however, beats the crocodile in one attempt. Next, a crocodile is eating at a table in the swamp that has birds next to it. It puts catchup on the birds and eats them one by one with a fork. A bigger crocodile takes a cow into the swamp, but the cow defeats the crocodile and comes out. Next, a goat is swimming away from a crocodile, clearly scared. The swamp suddenly dries out. The crocodile cannot walk fast, but the goat happily leaves the swamp. Then, a crocodile attacks a cow that is by the swamp, but the cow skins the crocodile and takes it for tanning. Next, a crocodile with dental braces is shown drinking with a straw. A baby zebra plays by the swamp and bothers the crocodile. After that, a crocodile is shown participating in a non-violence resistance group with other animals, holding a peace sign. The movie ends with a scene of a very long crocodile on which a bird is happily picnicking.

Linear storyline

The movie depicts a linear life story of a pig. It starts by showing a caterpillar on a leaf. Then a big sow appears and gives birth to seven piglets. The piglets follow the sow in a line going around woods and crossing roads. Two of the pigs suddenly disappear; they were killed on the road. The rest of the piglets also disappear one by one, except for one. Then the caterpillar is making a cocoon – showing the passage of time. The piglet grows up to be an ugly boar, and the sow is old. The sow dies. The pig meets three gilts. They reject him (depicted as a computer error message box) because he does not have money, he is ugly, and one of the gilts is already married. The cocoon is now complete, and the boar is still sad and alone. He bumps into a lion that was hunting for zebras. The lion gets happy for the catch, but the boar is too smelly. The lion puts the boar in a washing machine. He comes out as a red boar which is not desirable to the lion. The lion dumps the boar. The boar passes by the gilts again. This time, the one that was interested in a good-looking boar is interested and follows him.