# Time-Conjunctive Representations Of Future Events

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## Abstract

It is widely accepted that people can predict the relative imminence of future events. However, it is unknown whether the timing of future events is represented using only a "strength-like" estimate or if future events are represented conjunctively with their position on a mental timeline. We examined how people judge temporal relationships among anticipated future events using the novel Judgment of Anticipated Co-Occurence (JACO) task. Participants were initially trained on a stream of letters sampled from a probabilistically repeating sequence. During test trials, the stream was interrupted with pairs of probe letters and the participants' task was to choose the probe letter they expected to appear in the stream during a lagged target window 4-6 items (4.3-8.5 seconds) in the future. Participants performed above chance as they gained experience with the task. Because the correct item was sometimes the more imminent probe letter and other times the less imminent probe letter, these results rule out the possibility that participants relied solely on thresholding a strength-like estimate of temporal imminence. Rather, these results suggest that participants held 1) temporally organized predictions of the future letters in the stream, 2) a temporal estimate of the lagged target window, and 3) some means to compare the two and evaluate their temporal alignment. Response time increased with the lag to the more imminent probe letter, suggesting that participants accessed the future sequentially in a manner that mirrors scanning processes previously proposed to operate on memory representations in the short-term judgment of recency task.

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# Introduction

*"It is perfectly true, as the philosophers say, that life must be understood backwards. But they forget the other proposition, that it must be lived forwards."* - *Søren Kierkegaard* (Kierkegaard, 1938)

The capacity for prospection is the guiding force of human action. By accurately representing the future, we can imagine how events will unfold and can make decisions accordingly in the present: if I want to become a doctor in the future, I must study physiology now; if I want to be healthy in my old age, I must exercise and eat properly now; if I want to send my children to university, I must save for that expense now. This is true of shorter time scales as well: moment-to-moment predictions of upcoming stimuli help guide perception, action, and learning, and may be a fundamental aspect of cognitive function (Clark, 2013).

Prospection, short- or long-term, has been argued to rely on some of the same cognitive processes that support memory (Tulving, 1985a). A number of studies have demonstrated that the neural bases of these processes overlap (Atance & O'Neill, 2001; Addis, Wong, & Schacter, 2007; Schacter, Addis, & Buckner, 2007; Szpunar, Watson, & McDermott, 2007; Bar, 2009; Spreng, Mar, & Kim, 2009), suggesting that simulation of an event, whether experienced (past) or imagined (future), relies on brain structures such as the medial temporal lobe (Okuda et al., 2003) and ventromedial prefrontal cortex (Hassabis & Maguire, 2007). Prospection is impaired in amnesia (Tulving, 1985b; Klein, Loftus, & Kihlstrom, 2002; Kwan, Carson, Addis, & Rosenbaum, 2010), the level of detail in prospective and remembered experiences is correlated across individuals (Williams et al., 1996), and prospective simulations are more detailed when more relevant memory details are available (Szpunar & McDermott, 2008).

An outstanding question is whether time serves the same organizing role for prospection as it does for memory. Episodic memory prominently includes information about the time at which events occurred: the accuracy and latency of memory retrieval depends on recency (Shepard & Teghtsoonian, 1961; Monsell, 1978; Glenberg et al., 1980; Hockley, 1982; Donkin

& Nosofsky, 2012) and temporal contiguity effects in free recall imply that remembered events are bound to a temporal context, which is retrieved with an event and serves as a cue for adjacent events (Murdock, 1962; Murdock & Okada, 1970; Murdock & Metcalfe, 1978; Kahana, 1996). Response times in the short-term judgment of recency task, in which participants judge which of two probe items occurred more recently in a stimulus stream, are consistent with a self-terminating backward scan along a temporally ordered memory representation (Muter, 1979; Hacker, 1980; Hockley, 1984; McElree & Dosher, 1993). These findings collectively imply a temporal axis along which events in memory are ordered and accessed.

There is some evidence already that future events, like past events, are represented along a temporal axis. Imagined future events are weaker and less detailed if they are temporally more remote, like a mirrored future-analogue of forgetting (D'Argembeau & Van der Linden, 2004). Rewarding events are discounted according to their anticipated delay (Samuelson, 1937; Frederick, Loewenstein, & O'Donoghue, 2002), and episodic prospection has incidental effects on temporal discounting (Peters & Büchel, 2010; Daniel, Stanton, & Epstein, 2013; Liu, Feng, Chen, & Li, 2013). At a neural level, theoretical work on temporal processing predicts the existence of temporally ordered future representations (Shankar, Singh, & Howard, 2016; Tiganj, Gershman, Sederberg, & Howard, 2019).

In the present investigation, we tested the temporal organization of future event representations by asking participants to judge temporal relationships among independent anticipated events in the near future. This form of near-future prospection is analogous to the near-past memory utilized in the judgment of recency task. To establish a predictable future, we created a series of stimuli that followed a regular sequence, analogous to a schematic script (Abelson, 1981) or the sequence learning that occurs in serial reaction time tasks (Willingham, Nissen, & Bullemer, 1989). Other recent work using a similar sequentially organized environment has demonstrated that people can successfully judge which of two stimuli is more imminent, a future-oriented analogue to judgments of recency. Singh and Howard

(2017) introduced a "judgment of imminence" task in which participants viewed a sequence of items with a pre-learned sequential structure, and were periodically asked to judge which of two probe items would occur sooner. That paper reported high accuracy for judgments of imminence, and analogous effects of a probe item's remoteness on response times for judgments of both imminence and recency. Here, we expanded on these judgments of imminence and tested participants' ability to make more complex judgments about which events would coincide with a specific time window in the future.

Our experiment was designed to assess two alternative ways in which the timing of future events could be cognitively represented. One possibility is that an event's temporal proximity is represented by a strength-like scalar. Strength-like representations of the timing of events have a role in a number of models of memory and reward anticipation (Hinrichs, 1970; Wickelgren, 1970; Sutton & Barto, 1981; Schultz, Dayan, & Montague, 1997), although such strength models have been unable to explain important empirical results in the memory domain (Hintzman & Block, 1971; Hintzman, Block, & Summers, 1973; Hintzman, 2010). In our task, merely thresholding a scalar, strength-like representation of an event's temporal proximity would not support successful performance, because the task was equally likely to require selecting the more- or less-imminent item. Successful performance in the present task would suggest, alternatively, that future events can be cognitively represented in conjunction with their position on a prospective mental timeline. Such a temporally organized representation of future events could permit sequential scanning along the timeline, enabling participants to imagine the future as it would unfold through time and judge which future events are expected to co-occur.

## Methods

Participants were recruited using Boston University's student jobs website. The advertisement informed participants that they would complete a one-hour cognitive task on a

computer and would be compensated \$12 for their time. Once in the lab, participants were informed that they would receive additional compensation based on their performance on the task (\$0.15 per correct response, \$6.00-\$12.75 per participant). 13 participants (aged 18-25, 9 female) were recruited as an initial sample. We proceeded to recruit a second sample of 13 participants (aged 18-28, 10 female) as a replication test of the results from the first 13. From this second data set, one participant's data file was mistakenly written to a non-existent directory, losing the data and leaving us with 12 participants in our replication sample.

Participants completed the task on a Macbook Pro running OS X El Capitan (version 10.11.6). The experiment was written in Python using PsychoPy2 version 1.85.1 (Peirce, 2007). Participants completed the task individually in a testing room under the supervision of the primary author.

The Judgment of Anticipated Co-Occurence (JACO) task required participants to make predictions about the future temporal overlap of 2 predictable events, a probe letter and a lagged target window. Participants were told that they would view a stream of letters, consisting of a repeating sequence of 15 letters which usually progressed in a fixed order but occasionally jumped to a random point in the sequence before continuing in order (Fig. 1). Letters were viewed one at a time for 1.2 seconds with a 0.2 second blank inter-item interval. Participants completed 4 task blocks (1 training block and 3 testing blocks) which lasted approximately 12 minutes each.

In the training phase (Block 1), participants first viewed the stream of letters for 4 minutes during which they were instructed to learn the sequence. After these 4 minutes, the stream was occasionally interrupted by a 2-alternative forced-choice trial that prompted the participant to predict the next letter in the stream. The visual prompt showed an empty purple square in the center of the screen where the stream letter normally appeared, flanked by 2 probe letters. One of these 2 probe letters was the next letter in the learned sequence (the target) and the other letter was not (the lure). Across the 15 trials in the training phase,
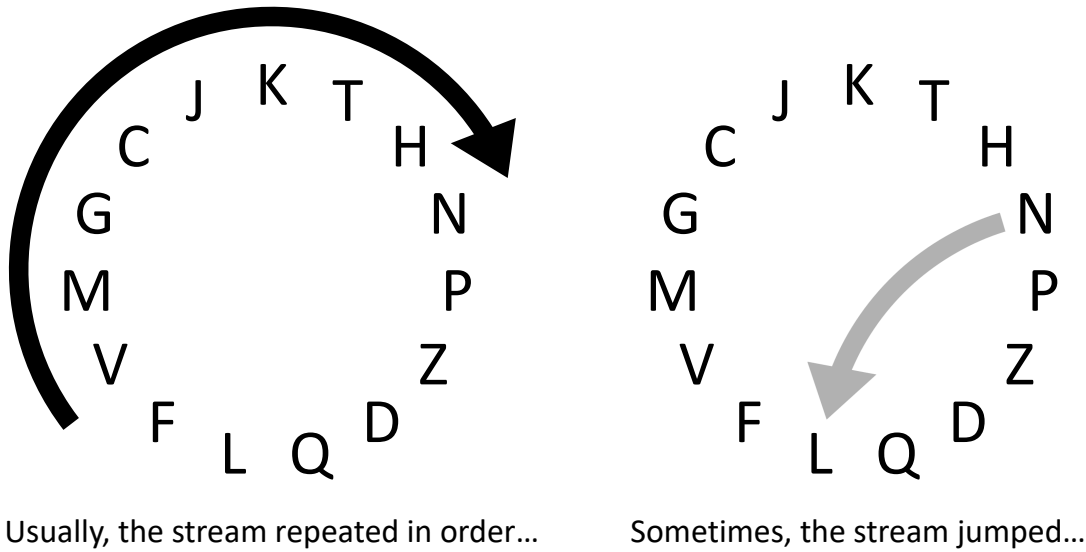
Figure 1: The stream proceeded in a patterned way. Usually, the stream proceeded in the order of the sequence. Shortly before each trial, the stream would jump to an unpredictable point in the sequence. After the jump, the stream proceeded in the order of the sequence until the trial was over.

each letter in the sequence appeared once as a target and once as a lure. Targets and lures were paired randomly, with the constraint that a lure could not be adjacent in the sequence to its corresponding target. Participants had up to 4 seconds to respond by pressing the left or right arrow key. After the response, the chosen probe letter and the purple square remained on the screen while the next letter of the stream was presented. If the next letter matched the chosen probe letter, participants heard a "ding," signifying that $0.15 had been added to their earnings.

In the testing phase (Blocks 2, 3, and 4), the participants' task was to judge which letter would appear during a lagged target window, which encompassed the letters at lags 4, 5, and 6 in the future (Fig. 2). Before the testing phase, participants saw a short instructional example that showed the behavior of the lagged target window. The visual prompt for trials showed an empty yellow square in the center of the screen flanked by 2 probe letters; a target, which would occur within the lagged target window, and a lure, which would occur within 2 letters before or after the window (lags 2, 3, 7, or 8). As in the training phase, participants had up to 4 seconds to respond. After the response, the chosen probe letter

remained on the screen but the yellow square disappeared as the stream progressed through lags 1, 2, and 3. After lag 3, the yellow square reappeared and remained through lags 4, 5, and 6. After lag 6, the chosen probe letter and the yellow square disappeared for good. If the chosen probe letter matched a letter that appeared in the stream while the yellow square was visible, participants heard a "ding," signifying that $0.15 had been added to their earnings.
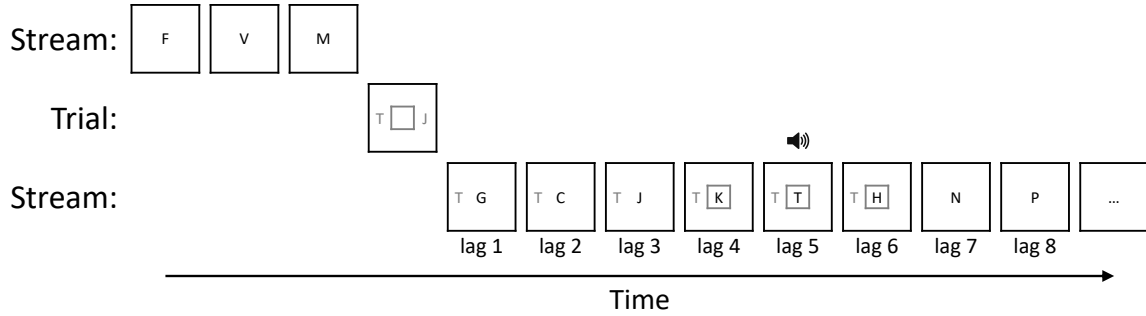


Figure 2: A sequence of screens showing what the participant would see on a correctly answered trial in the testing phase. The auditory cue occurred only if the stream letter matched the chosen probe letter while the square was on the screen; the cue represented earnings of $0.15.

In the testing phase, the stream had the same sequential structure as it did in the training phase (Fig. 1). Eight letters after each trial, the sequence jumped to a point 4 to 7 letters before where the next trial would appear. This resulted in jumps ranging from 0 to 14 letters. The jumps served to decouple recent past experience from future predictions, so responses could not be reliably guided by the relative recency of the 2 probe items (Fig. 3). Participants were invited to take short breaks between blocks.
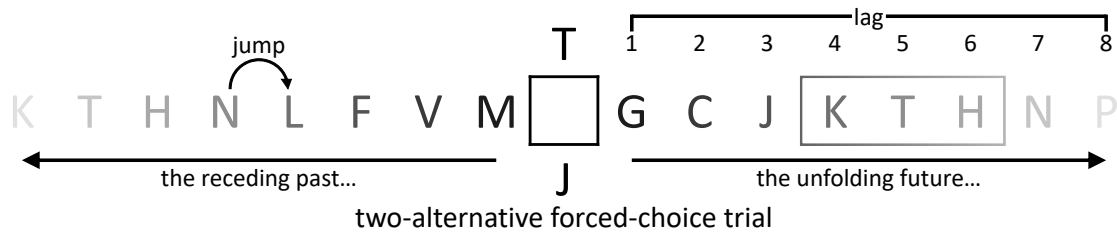


Figure 3: A hypothesized internal representation during the testing phase. When a trial occurred, the participant judged which of the 2 probe letters would occur in the lagged target window, using the remembered past to orient placement in the sequence and a simulated future to access relevant representations of future events.

For each pair of probe letters, a target at lag 4, 5, or 6 positions in the future was paired

with a lure at lag 2, 3, 7, or 8 positions in the future with the constraint that the target and lure were not adjacent in the sequence. Probe letters were limited to forward lags 1-8 so that each probe letter's forward-looking lag was shorter than or equal to its backward-looking lag within the learned sequence (for example, forward lag 7 is equivalent to backward lag 9 in our 15-letter sequence). Given these criteria, 45 unique probe letter pairings were possible. From these pairings, we created 90 trials such that each unique pair was presented twice, and each probe letter within the pair was a target once and a lure once. This trial-construction scheme ensured that each sequence letter, when presented as a probe letter, was equally likely to be a target or lure and equally likely to be the more or less imminent of the 2 probe letters. We further arranged a relatively uniform sampling of all possible target-lure lag combinations. The 90 trials were randomly shuffled, and each of Blocks 2, 3, and 4 contained 30 trials.

All analyses were written in R (version 3.5.1) using RStudio (version 1.1.453). All figures were created using the same software. Packages were used to calculate effect sizes (Navarro, 2015), do power analyses (Champely, 2018), draw scatterplots (Eklund, 2016), create mixed-effects regressions (Bates, Maechler, Bolker, & Walker, 2015), plot confidence intervals (Lemon, 2006), execute variance and closeness tests (Merkle & You, 2018; Wang & Merkle, 2018), and make hierarchical Bayesian models (Bürkner, 2017; Carpenter et al., 2017; Bürkner, 2018; Stan Development Team, 2018).

# Results

The response on each trial was categorized as correct, incorrect, or missed (no response). All analyses presented hereafter consider only trials with responses. Missed trials (18.1% in training phase; 2.31% in testing phase) were excluded from subsequent analyses.

## Training-phase accuracy

Training phase performance (Block 1) was above chance, indicating that participants learned the sequence. Group accuracy was significantly above chance ($p < 0.001$, 2-sided Wilcoxon signed-rank test) with a median accuracy of 71.4% ($\sigma = 15.5\%$; Fig. 4a). The effect of trial number on accuracy was not significant ($p = 0.155$, mixed-effects probit regression), but by the end of the block the estimated mean accuracy was 84.0% (mixed-effects probit regression; Fig. 4b). Mean response time was 1.35 seconds ($\sigma = 0.687$).
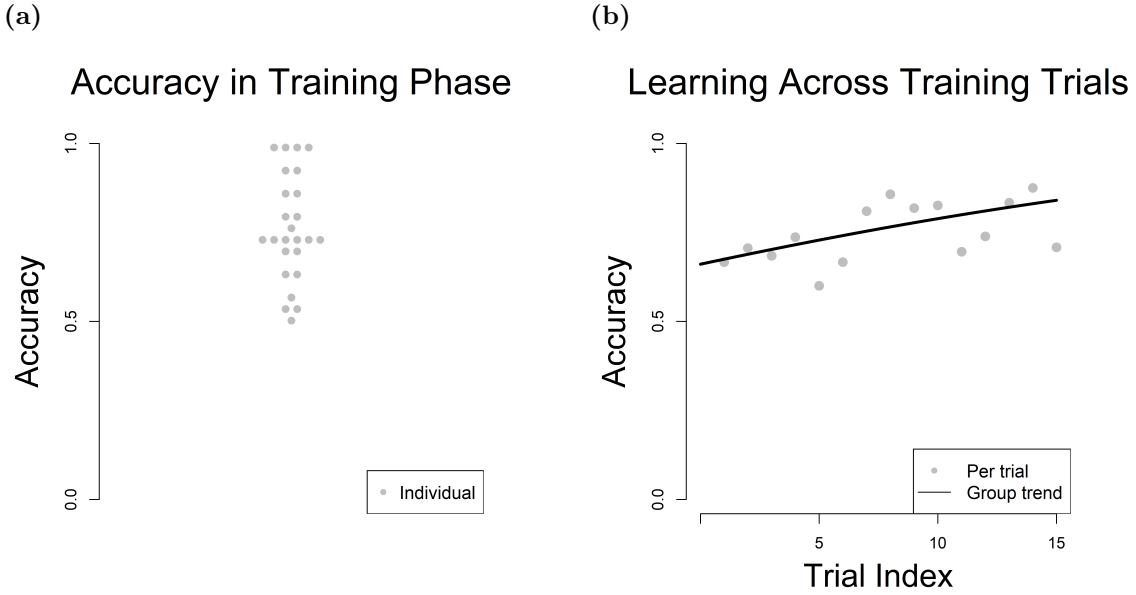
**(a)**  **(b)**



Figure 4: Participants learned the sequence during training (Block 1). **(a)** As a group, participants performed significantly above chance on training trials ($p < 0.001$, 2-sided Wilcoxon signed-rank test). The y-axis shows accuracy. Median participant accuracy was 71.4% ($\sigma = 15.5\%$). **(b)** Accuracy over the course of the block. The x-axis shows the trial number and the y-axis shows accuracy. By the end of training, estimated mean accuracy was 84.0% (mixed-effects probit regression).

## Testing-phase accuracy

Accuracy increased over the course of the testing phase (Blocks 2, 3, and 4), indicating that participants learned how to complete the task. Similar trajectories were observed in both samples (Table 1).

In Block 4, group accuracy was significantly above chance in both samples ($p = 0.004$ and

No participants performed below chance in Block 4. Due to the performance similarities between the two samples, subsequent analyses consider only the combined sample.

Participants exhibited progressively increasing accuracy across trials, and there was a significant effect of trial number on accuracy ($p < 0.001$, mixed-effects probit regression; Fig. 5b). Estimated mean accuracy ranged from 49.3% at the start of the testing phase to 69.5% at the end of the testing phase (mixed-effects probit regression). The group-level probit fit can be interpreted in terms of a linear change in the sensitivity index ($d'$) as a function of trial number (DeCarlo, 2012): the estimated sensitivity index ranged from -0.025 at the start of the testing phase to 0.720 at the end of the testing phase. Comparing accuracy rates from the training block (Block 1) and the last testing block (Block 4), we found a weak positive correlation ($\rho = 0.186$, $p = 0.385$, Spearman), indicating that we could neither strongly confirm nor rule out an association between training success and task performance.

## Response time and accuracy by lag

We tested the hypothesis that future-event representations were accessed via a self-terminating forward scan along a temporally ordered prospective representation of the stimulus sequence, akin to scanning processes that have been proposed to operate in short-term judgment of recency tasks (Muter, 1979; Hacker, 1980; Hockley, 1984; McElree & Dosher, 1993). The scanning process is assumed to proceed forward from the present time, serially examining each anticipated item and terminating when either the target or lure is encountered, whichever comes first. The scanning hypothesis predicts an increase in response time as a function of the lag to the more imminent of the two probe items. Previous studies of retrospective scanning processes suggest that the increase in response time as a function of lag is sublinear, indicating that scanning takes place along a compressed timeline of events (Brown, Neath, & Chater, 2007; Howard, Shankar, Aue, & Criss, 2015; Singh & Howard, 2017).

To focus on the mechanisms of successful task performance, analyses of response times

were restricted to correct trials in Block 4. The analyses were carried out both for the full sample (Figs. 6a-b) and a subset of high-performing individuals ($>66.7\%$ accuracy, $n = 8$; Figs. 6c-d), based on the assumption that error rates imply a similar number of trials could have been correct by chance.

Response times increased as a function of the lag to the more imminent probe letter (Figs. 6a, 6c). This effect was consistent with the hypothesized self-terminating forward scan along a temporally ordered prospective representation of the stimulus sequence. The effects of lag and log lag on response time were significant for the full sample ($p < 0.001$, mixed-effects linear regression) and the high-performing subset ($p < 0.005$, mixed-effects linear regression). As the linear and logarithmic models were non-nested, we used Vuong's method to determine whether the models were distinguishable and, if so, which one more closely fit the data (Vuong, 1989). The difference in fit between the linear and logarithmic models was not significant, either in the full sample ($p = 0.311$, Vuong's closeness test) or in the high-performing subset ($p = 0.238$, Vuong's closeness test), although the models were distinguishable in both cases ($p = 0.018$ & $p = 0.011$, Vuong's variance test).

To determine if response times also changed as a function of the lag to the *less* imminent probe letter, we appended this additional predictor to the regression models described above. In the full sample, log lag to the more imminent probe letter remained a significant predictor ($p = 0.020$, mixed-effects linear regression) whereas log lag to the less imminent probe letter was not ($p = 0.919$, mixed-effects linear regression). The two-predictor model generally returned higher-variance parameter estimates because balancing the relative imminence of targets and lures (an essential feature of our experimental design) produced a positive correlation between the lag to the more-imminent and less-imminent item in each probe pair ($\rho = 0.828$, $p < 0.001$, Spearman). The Akaike information criterion indicated the superiority of the simpler model which only used lag to the more imminent probe letter as a predictor ($\Delta AIC = 3.99$). In the high-performing subset, neither term in the two-predictor regression model was statistically significant, but the Akaike information criterion

(a)

Response Times by Lag
(All Participants)



(b)

| Accuracy by Lag Pairing | | | |
|---|---|---|---|
| All | Lag to Target | | |
| Participants | 4 | 5 | 6 |
| 2 | 0.71 | 0.75 | 0.77 |
| Lag 3 | — | 0.56 | 0.61 |
| to — | | | |
| Lure 7 | 0.60 | 0.57 | — |
| 8 | 0.67 | 0.65 | 0.71 |

(c)

Response Times by Lag
(High Performers)



(d)

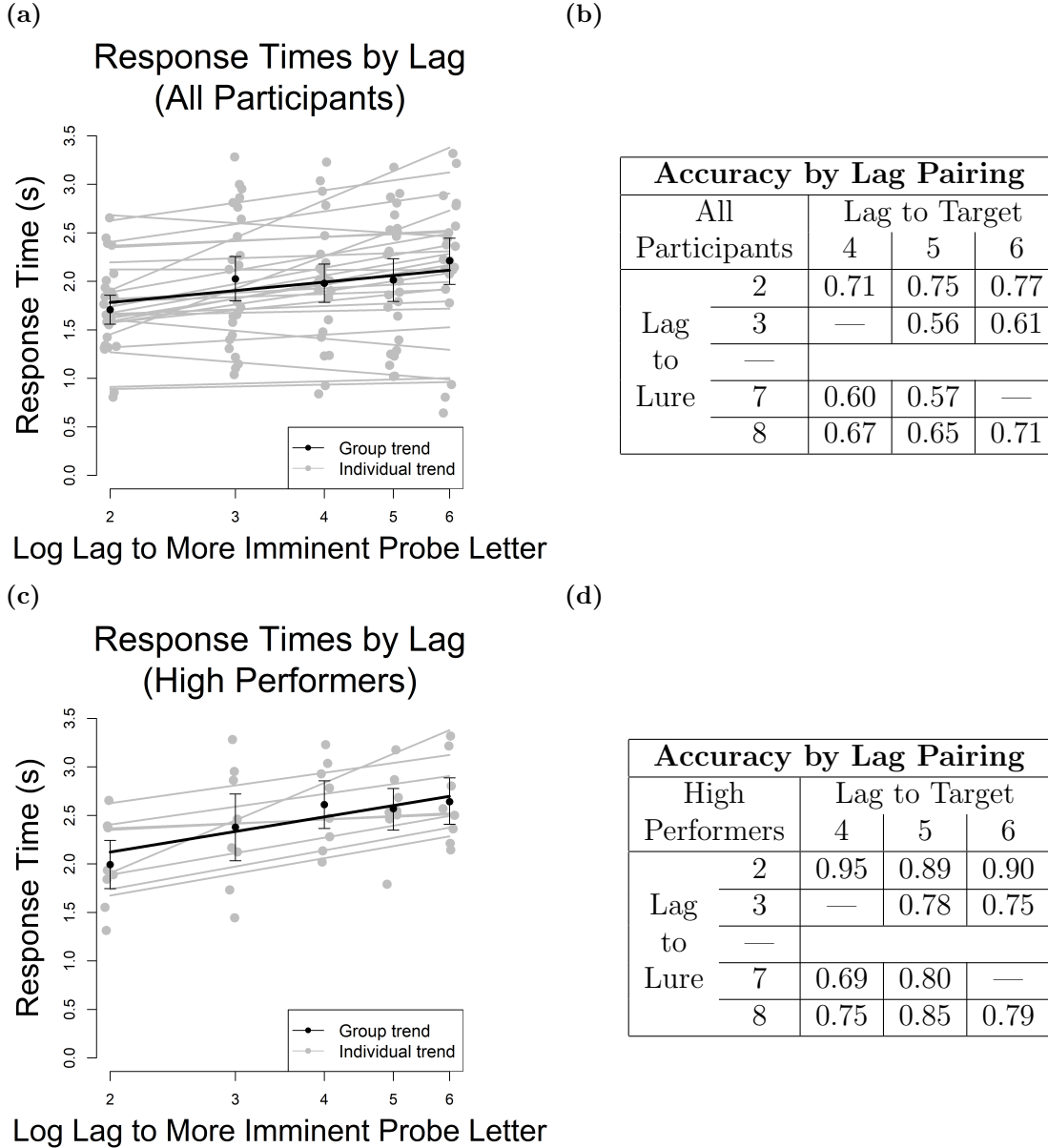| Accuracy by Lag Pairing | | | |
|---|---|---|---|
| High | Lag to Target | | |
| Performers | 4 | 5 | 6 |
| 2 | 0.95 | 0.89 | 0.90 |
| Lag 3 | — | 0.78 | 0.75 |
| to — | | | |
| Lure 7 | 0.69 | 0.80 | — |
| 8 | 0.75 | 0.85 | 0.79 |

Figure 6: **(a)** Response time increased with the lag to the more imminent probe letter. The x-axis shows the log lag to the more imminent probe letter and the y-axis shows response time. Data are from final testing block (Block 4) trials which were correctly answered ($n = 25$). Median response times are shown for individuals and means of medians are used for the group. Confidence intervals (95%) were calculated using bootstrap of the mean. The increase in response time with respect to the lag to the more imminent item was consistent with a self-terminating forward scan. **(b)** Accuracy was influenced by whether lures were further from the window (lags 2 and 8) or nearer (lags 3 and 7; $p = 0.003$, mixed-effects probit regression). Data are from final testing block (Block 4) trials ($n = 25$). **(c, d)** Equivalent results were observed in analyses restricted to high-performing participants ($n = 8$), both for response times **(c)** and accuracy **(d)**.

again favored the simpler model ($\Delta AIC = 2.70$).

Accuracy was influenced by whether the lure was nearer to the target window (lure lag

3 or 7) or further from it (lure lag 2 or 8). We analyzed accuracy as a function of three categorical factors: inner/outer lure position (lag 3 or 7 vs. lag 2 or 8), early/late lure position (lag 2 or 3 vs. lag 7 or 8), and inner/outer target position (lag 5 vs. lag 4 or 6). We observed a significant effect on accuracy of inner/outer lure position ($p = 0.003$) and no effect of early/late lure position ($p = 0.165$) or inner/outer target position ($p = 0.786$; Fig. 6b). The high-performing subset ($n = 8$) showed a similar pattern, with a significant effect on accuracy of inner/outer lure position ($p = 0.050$) and no significant effects of the other factors (Fig. 6d).

## Testing alternative explanations

Finally, we considered the alternative possibility that accuracy increased across trials due to some form of stimulus-based reinforcement learning that did not require accessing a representation of the future. If a simple form of reinforcement learning were a viable strategy, then participants might have been able to attain above-chance accuracy without relying on a time-conjunctive representation of future events.

The task was designed to rule out a simple reinforcement learning strategy operating on individual probe letters. Each letter appeared as a probe item a total of 12 times: 6 times as a target and 6 times as a lure. Therefore, a strategy of preferentially selecting previously rewarded probe letters would not yield above-chance performance. The design also ruled out a simple strategy of learning to select the more recently encountered item (or the less recently encountered item). The stream jumped to a new point in the sequence before each trial, decoupling an item's recency from its imminence and resulting in a distribution of relative recency (target recency minus lure recency) that was symmetric around zero. The participant-level median relative recency ranged from -2 to +2, with no systematic bias (p=0.305, 2-sided Wilcoxon signed-rank test).

Another potential reinforcement learning strategy would act on sets of paired probe letters. Each unique pair of probe letters was presented twice during the experiment. The

2 presentations occurred at different points in the sequence such that each of the 2 probe letters in the pair was a target once and a lure once. Therefore, it is possible, if implausible, that if participants remembered which letter was the target during the first presentation of a pair, they could perfectly predict that the other letter would be the target in the second presentation of the same pair.

To evaluate this possibility, we examined accuracy rates on first and second presentations of a given probe letter pair separately as a function of trial index (Fig. 7). We did not observe any significant difference in performance between the 2 presentations, neither in the intercept ($p = 0.815$, mixed-effects probit regression) nor in the slope of the learning effect ($p = 0.680$, mixed-effects probit regression). A hierarchical Bayesian model using standard normal priors yielded evidence ratios favoring no difference in the intercept ($BF = 7.12$) nor in the slope of the learning effect ($BF = 3.94$). These results suggests it is unlikely that above-chance performance can be accounted for in terms of stimulus-based reinforcement learning.
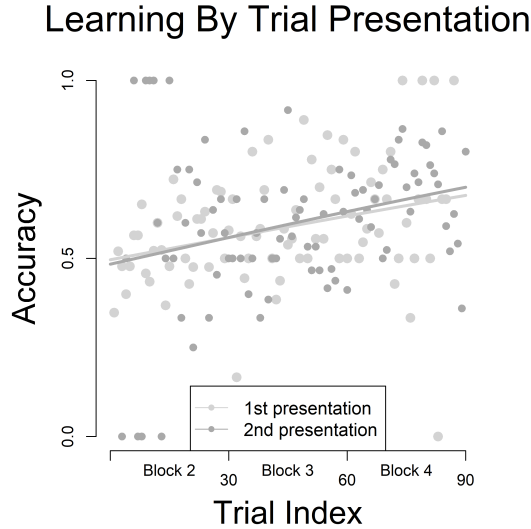


Figure 7: Learning over the course of the experiment was not attributable to stimulus-based reinforcement learning acting on sets of paired probe letters. The x-axis shows the trial number and the y-axis shows accuracy. Points show the group-level accuracy on that trial number broken into first and second presentations of paired probe letters. No significant differences in the intercept ($p = 0.815$, $BF = 7.12$, mixed-effects probit regression) or in the slope of the learning effect ($p = 0.680$, $BF = 3.94$, mixed-effects probit regression) were observed between the two sets of trials.

# Discussion

We investigated how the timing of future events is cognitively represented. To do this, we developed the novel Judgment of Anticipated Co-Occurrence (JACO) paradigm, which required participants to predict the temporal overlap of future events. The task was designed to test whether future events are held in conjunction with their position on a prospective mental timeline, or whether they are represented with a strength-like signal indicating relative imminence. We further used response times to examine the mechanism by which the future is accessed, hypothesizing that participants would imagine the future as it unfolded through time and that response times would scale with the lag to the more imminent probe letter.

Participants' group-level performance in the task was significantly above chance, and a subset of participants performed significantly above chance as individuals. Successful task performance could not be explained by a strength-like estimate of future timing coupled with a linear decision process. Participants' behavior implied they were equipped with 1) temporally organized predictions of the future letters in the stream, 2) a temporal estimate of the lagged target window, and 3) some means to compare the two and evaluate their temporal alignment. Our results suggest that people can construct a timeline of near-future events based on their past experiences and subsequently access and reason about this constructed time-conjunctive future.

This result is inconsistent with the notion that predictions are made and acted upon using a scalar, strength-based estimate of future timing coupled with threshold-like decision process. Due to the placement of targets and lures, task performance using temporally discounted signal-strength would have been at chance level, as targets were equally likely to be more or less imminent than their associated lures. The balanced relative imminence of targets and lures would also present difficulties for an account in which judgments were based on the instantaneous rate of change in signal-strength (McLaren, 1994). Reconciling our findings with a strength-like representation of temporal proximity would require a more

complex, nonlinear decision process, one that could select items with strength (i.e., immi-nence) in a specific, delimited range. If such a windowing operation were possible, strength would effectively serve to represent an item's position on a future-oriented mental time line and would constitute a time-conjunctive representation.

Even though full information to support task performance was available at the beginning of the testing phase, participant accuracy began near chance and increased across testing trials. Before the testing phase began, participants had learned the sequence reasonably well and had been presented with the deterministic behavior of the lagged target window. One possible explanation for higher performance over time is that participants continued to build more accurate representations of the sequence and the lagged target window. Future studies might test this possibility by including longer periods of training or intermediate checks on the accuracy of participants' representations. Another possible explanation is that over time, participants gained facility with the evaluation of temporal co-occurrence. The improvement in accuracy over time did not appear to be attributable to stimulus-based reinforcement learning. Likewise, we regard it as implausible that participants succeeded at the task by independently learning pairwise associations between sequence positions and target items, given that each of the 45 position-target pairings occurred a maximum of three times in the experiment and such an account would not explain the observed effects of lure position on accuracy and response time. It is possible that with extensive additional training on a single sequence, participants would be able to use a task-specific shortcut based on direct associative retrieval of the three possible targets for every possible probe position, reducing their reliance on a temporally organized representation of the future. Such a shift would resemble the transition to automaticity that occurs after numerous item repetitions in an "alphabet arithmetic" task (Logan & Klapp, 1991; Klapp, Boches, Trabert, & Logan, 1991).

Participant accuracy varied with the positioning of events in the future timeline, suggest-ing the existence of a temporal dimension along which events are located and differentiated. Accuracy was greater when the lure was further from the lagged target window (lures at

lags 2 and 8) than when it was closer to the lagged target window (lures at lags 3 and 7). Accuracy was greatest for trials with lures at lag 2, suggesting that the nearest future was accessed with the most clarity. The placement of the target did not meaningfully affect accuracy, nor did whether the lure preceded or followed the target.

If a participant's imagined episodic future were sequentially accessed during trials, one would expect response times to increase in tandem with the temporal remoteness of the information necessary to support accurate decisions. That is precisely what was seen in the response time data, as response time increased with the lag to the more imminent probe letter. These results parallel findings in the memory and prospection literature, and are consistent with the notion of a self-terminating forward scanning process (Muter, 1979; Hacker, 1980; Hockley, 1984; McElree & Dosher, 1993; Singh & Howard, 2017).

Our response time data were not consistent with a theoretical "jump forward in time" similar to the "jump back in time" that characterizes episodic memory (Howard & Kahana, 2002). Response times were inconsistent with participants jumping forward in time to the lagged target window, the target region of interest. If such a process were used, we would not expect response times to increase with the lag to the more imminent probe letter; rather, we would expect them to remain constant or to vary with the lag to the target.

There are numerous questions still remaining about the flexibility of episodic prospection; variants of the present task could be used to test those hypotheses in future research. One outstanding question is whether the pattern of accessing the future depends on which temporal region of the future is relevant. One could run this task with a variety of different lagged target windows to test participants' ability to switch flexibly among them, and to test whether the dynamics of the forward scanning process remain the same at longer timescales. Another open question is whether the future is simulated continuously through time or as an ordinal succession of discrete events. To test this, one could deconfound time and ordinal position, which are interchangeable in the present version of the paradigm. Using temporally jittered item presentations or a continuously evolving stimulus would make it possible

to determine whether the future is imagined continuously through time or as an ordinal succession of discrete events.

A fundamental difference between the past and the future relates to the nature and degree of uncertainty associated with the represented sequence of events. Whereas past events may be subject to epistemic uncertainty (if, for instance, they are imperfectly remembered), the future can be uncertain because stochastic events have yet to be realized, sometimes called "aleatoric" uncertainty (Tannenbaum, Fox, & Ülkümen, 2017). Here we used events with a largely deterministic sequential structure in order to establish a predictable future, in contrast with the unpredictable sequences typically used for testing judgments of recency. An important goal for future research will be to examine how temporally organized future event representations would operate in environments with less deterministic structures, such as where future events could follow either of two possible trajectories. It would also be of interest to compare judgments of recency in the context of novel versus well-learned sequences.

Our results demonstrate that people can craft a time-conjunctive representation of the near future informed by past experience, which has well-ordered temporal characteristics and is accessed sequentially. These results add to the existing body of evidence for a system of episodic prospection that mirrors episodic memory.

**Open practices statement:** Experimental script, data, and statistical analyses are available at `https://github.com/cd-lab/JACO`. The experiment was not preregistered.

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