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Relational Processing Demands and the Role of Spatial Context in the Construction of Episodic Simulations

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Reports on differences between remembering the past and imagining the future have led to the hypothesis that constructing future events is a more cognitively demanding process. However, factors that influence these increased demands, such as whether the event has been previously constructed and the types of details comprising the event, have remained relatively unexplored. Across two experiments, we examined how these factors influence the process of constructing event representations by having participants repeatedly construct events and measuring how construction times and a range of phenomenological ratings changed across time points. In Experiment 1, we contrasted the construction of past and future events and found that, relative to past events, the constructive demands associated with future events are particularly heightened when these events are imagined for the first time. Across repeated simulations, future events became increasingly similar to past events in terms of construction times and incorporated detail. In Experiment 2, participants imagined future events involving two memory details (person, location) and then reimagined the event either (a) exactly the same, (b) with a different person, or (c) in a different location. We predicted that if generating spatial information is particularly important for event construction, a change in location will have the greatest impact on constructive demands. Results showed that spatial context contributed to these heightened constructive demands more so than person details, consistent with theories highlighting the central role of spatial processing in episodic simulation. We discuss the findings from both studies in the light of relational processing demands and consider implications for current theoretical frameworks.

Keywords: autobiographical memory, future thinking, scene construction, Bayesian modeling

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Data and scripts to reproduce all analyses and figures are publicly available at osf.io/xqm5n.

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The data are available at https://osf.io/xqm5n/.

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Episodic simulation refers to constructing a mental representation of a specific autobiographical event, including future-oriented episodes (Szpunar, Spreng, & Schacter, 2014). In the past decade, research on episodic simulation has produced compelling evidence that this process is intimately related to episodic memory (for reviews, see Schacter et al., 2012, Schacter, Benoit, & Szpunar, 2017). Numerous studies have identified processes and properties that affect memories of the past and simulations of the future in very similar ways. For example, early neuropsychological studies described patients whose brain damage led to problems not just with episodic memory, but also with envisioning the future (e.g., Hassabis, Kumaran, Vann, & Maguire, 2007; Klein, Loftus, & Kihlstrom, 2002; Rosenbaum et al., 2005; Tulving, 1985). Furthermore, the brain networks underlying episodic memory and episodic simulation largely overlap (Addis, Wong, & Schacter, 2007), and qualitative changes in remembering past events during healthy aging, such as decreases in episodic details contained in remembered past events, are similarly apparent in episodic simulations (for a review, see Schacter, Gaesser, & Addis, 2013).

This close link between episodic memory and episodic simulation is captured theoretically by the constructive episodic simulation hypothesis (Addis, 2018; Roberts, Schacter, & Addis, 2018; Schacter & Addis, 2007), which proposes that when thinking about the future, details from episodic memory are extracted, recombined, and integrated into coherent events, thus allowing us to construct and simulate scenarios that have never occurred previously. According to the hypothesis, both episodic memory and episodic simulation are constructive processes, drawing on the same information (details from episodic memory) and the same underlying processes (construction and elaboration of the events), but episodic simulation additionally requires the flexible integration of episodic details into new, coherent representations.

This notion is consistent with recent findings of phenomenological, cognitive, and neural differences between episodic memory and episodic simulation. Studies have shown, for example, that imagined future events are less detailed (Addis, Wong, & Schacter, 2008; Berntsen & Bohn, 2010; D'Argembeau & Van der Linden, 2004, 2006; Gamboz, Brandimonte, & De Vito, 2010; Grysman, Prabhakar, Anglin, & Hudson, 2013; McDonough & Gallo, 2010), less coherent (D'Argembeau & Van der Linden, 2006; Grysman et al., 2013), less specific (Anderson & Dewhurst, 2009), and more difficult to generate (D'Argembeau & Van der Linden, 2004; McDonough & Gallo, 2010) than remembered past events. Evidence for future events taking longer to construct than past events in laboratory settings is quite sparse, however, with most papers finding no evidence for a difference in response times (Addis, Cheng, Roberts, & Schacter, 2011, Addis, Pan, Vu, Laiser, & Schacter, 2009, Addis et al., 2007; Botzung, Denkova, & Manning, 2008; D'Argembeau & Van der Linden, 2004; Spreng & Grady, 2010; Weiler, Suchan, & Daum, 2010b, 2011), although Anderson, Dewhurst, and Nash (2012) have shown an effect for highly imageable cues.

The evidence reviewed above suggests that episodic simulation is associated with additional cognitive demands likely related to constructing an event representation for the first time—as is the case with novel future events, which participants are typically instructed to construct "from scratch" in these experiments. For instance, a greater number of new associations between details are formed when constructing a novel representation (e.g., simulating a future event) relative to retrieving an existing representation (e.g., recalling a past event; Addis, 2018). As such, these constructive demands should decrease when an existing representation of a future event is reimagined. Preliminary evidence for this idea comes from two studies that manipulated the novelty of episodic simulations using repetition paradigms (Szpunar & Schacter, 2013; van Mulukom, Schacter, Corballis, & Addis, 2013). These studies showed that repeatedly imagining future events results in faster and increased ease of event construction, increased plausibility and levels of imagined detail, and reduced hippocampal activation, compared with the initial construction. However, both studies only examined the construction of future events. Previous evidence suggests that past events also become more vivid with increasing repetition (Svoboda & Levine, 2009) and are recalled faster when primed (Park & Donaldson, 2016); however, repeated future simulation has not been contrasted with the repeated recall of past events in the same experiment. Doing so would allow examination of whether the construction of episodic simulations is more demanding than retrieving memories per se, or whether constructive demands during simulations are particularly heightened when imagining a future event from scratch. Therefore, in Experiment 1, we adapted the repetition paradigm from van Mulukom et al. (2013) to include a condition in which memories of past events were recalled repeatedly, enabling us to compare directly the effects of repetition on construction times and levels of detail comprising past versus future events.

The second aim of this study was to establish the role different event components (i.e., episodic details types) play in the constructive process, with a particular focus on distinguishing between the relative contribution of spatial and nonspatial details. Although some argue that spatial context plays a central role in episodic simulations, providing the "stage" within which an imagined event unfolds (e.g., scene construction theory: Hassabis & Maguire, 2007; spatial scaffold effect: Robin, 2018), others contend that the construction of spatial contexts arises out of a general relational processing mechanism that is also responsible for the integration of other event details into the event representation (e.g., constructive episodic simulation hypothesis; Roberts et al., 2018).

Some progress has been made toward disentangling the differential effects of spatial and nonspatial details on various aspects of episodic simulation. Two lines of evidence suggest that spatial context may play a more central role than other event components. First, characteristics of the spatial context influence the quality of imagined future events, such that a more familiar spatial context is associated with higher levels of overall detail and clarity (Arnold, McDermott, & Szpunar, 2011; D'Argembeau & Van der Linden, 2012; de Vito, Gamboz, & Brandimonte, 2012; Robin & Moscovitch, 2014, 2017; Szpunar & McDermott, 2008), and that simulations with a clearer spatial context are perceived as being more likely to occur in the future (Ernst & D'Argembeau, 2017). Second, spatial context has been found to serve as a superior memory cue for imagined future events (Robin, Wynn, & Moscovitch, 2016). However, similar effects have also been reported for nonspatial details. It has been shown, for example, that the familiarity of nonspatial details, such as people (D'Argembeau & Van der Linden, 2012; McLelland, Devitt, Schacter, & Addis, 2015; Robin et al., 2016) and objects (D'Argembeau & Van der Linden, 2012) influence phenomenological aspects of episodic simulations, that person details result in more specific episodic simulations relative to when spatial contexts are used as cues to elicit imagined events (D'Argembeau & Mathy, 2011), and that there is no difference between person details and the spatial context of episodic simulations in terms of how well they are later remembered (Jeunehomme & D'Argembeau, 2017).

Taken together, the evidence does not seem stronger one way or the other with regard to whether spatial context plays a more central role in episodic simulation than other episodic details. However, if spatial context does indeed provide the stage for a simulated event, then the centrality of its contribution may be limited to the initial construction rather than the later elaboration of the simulated events. Indeed, Robin et al. (2016) observed that participants often spontaneously added spatial context at the beginning of the simulation process when the initial cue was something other than a location, while this spontaneous integration rarely occurred for other detail types (for a similar effect in episodic memory, see Hebscher, Levine, & Gilboa, 2018). In Experiment 2, we aimed to clarify these findings by directly manipulating the influence of spatial and nonspatial details (locations and people) on the construction of episodic simulations. Like in Experiment 1, participants repeatedly imagined future events involving key memory details. However, in this experiment, the future events to be reimagined were either exactly the same (no change), or featured a different person (person change), or were in a different location (location change). This allowed us to assess how a change in one component of the simulation affects its construction and the generated detail relative to when future events are reimagined without any changes, and critically, whether any effects are the same or different for spatial and nonspatial details.

The evidence reviewed above indicates that, theoretically, there are two equally plausible models (spatial and nonspatial detail changes disrupt repetition effects equally relative to the baseline condition vs. spatial context disrupts repetition effects more than nonspatial details relative to the baseline condition) that should be compared to the null hypothesis (no difference between any conditions). Therefore, we chose to use a Bayesian approach, which, unlike null hypothesis significance testing, enables a comparison of the evidence for alternative hypotheses against each other (rather than simply against the null), and additionally offers great flexibility in specifying and testing theoretically precise and constrained hypotheses (Etz, Haaf, Rouder, & Vandekerckhove, 2018; Fidler, Singleton Thorn, Barnett, Kambouris, & Kruger, 2018).

Experiment 1

The aim of Experiment 1 was to determine whether the construction of episodic simulations is more demanding than retrieving episodic memories per se, or whether episodic simulation is particularly demanding when imagining a novel event representation from scratch. To this end, we used a paradigm requiring participants to repeatedly recall past events and repeatedly imagine future events, while recording construction times (approximated by response times) and subjective ratings of how much detail was incorporated into the events. We predicted that the initial construction of future events (i.e., Time Point 1) would take longer than for past events, but that future event representations would nevertheless be less detailed. We also predicted that repetition effects would be evident for both past and future events, such that construction times would decrease, and detail ratings would increase, with repeated retrieval/simulation (i.e., across Time Points 1 to 3). Critically, if episodic simulation is always more demanding than episodic retrieval, any past-future differences evident during the initial time point should be maintained across repeated recall/simulation. However, if simulating an event from scratch is differentially more demanding, then the past-future differences should dissipate with repetition as future events become increasingly similar to past events with faster construction times and higher levels of incorporated detail.

Method

Participants. Twenty-three healthy young adults participated in this study and provided informed consent in a manner approved by the University of Auckland Human Participants Ethics Committee. All participants were fluent in English, had no history of neurological or psychiatric conditions or use of psychotropic medications, and had not participated previously in a study on episodic simulation. Three participants were excluded due to insufficient responses to future event simulations (<75% of trials). Thus, data from 20 participants (10 males, Aged 18–24 years, $M = 19.6$ years old) were analyzed.

Stimulus collection. The experiment consisted of two sessions (Figure 1). During Session 1 (stimulus collection), participants recalled 100 episodic memories; for each event, they provided a short description, the year of occurrence (later transformed into temporal distance in years from the present), identified a person, location, and object featuring in the event, and rated each memory detail for familiarity on a 4-point scale (1 = *unfamiliar*; 4 = *very familiar*). Participants were instructed that the memories had to be of specific events that occurred in the past 10 years (verified based on descriptions and dates provided), and the three details could not be duplicated across events (i.e., each particular detail could only be provided once across all 100 memories). Of the events meeting these criteria, we randomly selected 80 to create future event cues for Session 2 (experiment). Specifically, memory details were randomly sorted into person-location-object sets, where each of the three memory details came from different memories; cues for past event trials comprised the three details provided for a given memory. Note that the familiarity of detail sets (average across the three details) was slightly higher for the future ($M = 2.84$, $SD = 0.34$) than for the past condition ($M = 2.72$, $SD = 0.34$; $BF_{10} = 32.05$).

Procedure. Session 2 took place one to two weeks later ($M = 11$ days, $SD = 6.8$ days), during which participants completed the experiment. We used a version of the episodic recombination paradigm (Addis et al., 2009; see cognitiveatlas.org/task/id/trm_59ed1f7a0ac9c for a basic description), in which participants imagine future events comprising familiar components (locations, people, or objects). Participants saw a screen with an instruction ("recall past" or "imagine future"), as well as a person-location-object detail set. The task was to recall the past event specified by the presented detail set or to imagine a novel future event comprising all three details that might occur in a specific spatiotemporal context within the next five years. Participants indicated when they had constructed the event (i.e., when they had an event in mind) by pressing a button and then continued elaborating on the recalled or imagined event until the end of the 8-s trial. After each trial, detail (1 = *not detailed*; 4 = *very detailed*) and plau-

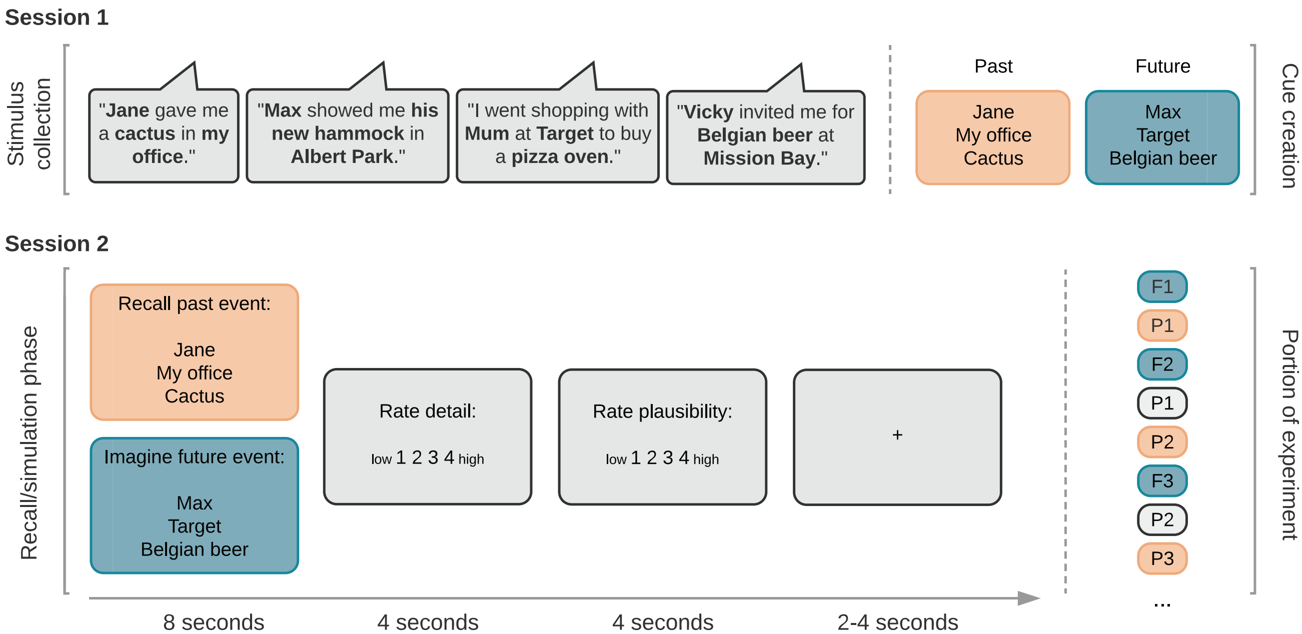

Figure 1. Stimulus collection: person, location, and object details featuring in memories were identified by participants. Cue creation: three details comprising a given memory (orange), or three details recombined across multiple memories (teal) were used for the past and future conditions, respectively. Recall/simulation phase: participants recalled past events and imagined future events and rated how detailed and plausible the events were. Future and past trials were presented at three time points within the same 60-trial block. See the online article for the color version of this figure.

sibility (1 = *implausible*, 4 = *very plausible*) ratings were made (4 s each).[1] Rating scales were followed by a fixation cross that was presented for a variable duration, ranging from 2 to 4 s. Critical for this experiment, every past and future detail set was repeated twice (Time Point 2, Time Point 3) after the first presentation (Time Point 1), that is, participants generated each event three times in total. During Time Points 2 and 3, participants were asked to recall/imagine the event from Time Point 1 without radically changing the event (such as progressing the event in time). These repeated presentations were identical in setup to Time Point 1 (cue followed by detail rating), except that plausibility ratings were not presented again. The experiment consisted of 40 detail sets per condition; each detail set was presented three times, resulting in a total of 120 time points (i.e., a trial comprising recall/simulation and rating scales) per condition. The experiment was divided into 4 blocks of 60 time points, which were presented in a pseudorandom order. The distance between corresponding time points was 1–4 trials (12–60 s, plus 2–4 s for fixation). The experiment was performed using Presentation software (Version 15.0, Neurobehavioral Systems, Inc., Berkeley, CA; www.neurobs.com).

Immediately after the experiment, participants were interviewed about the events they had remembered and imagined. Participants gave a short description of every event and rated their consistency across the three time points (4-point scale; 1 = *different*; 4 = *identical*), as well as the personal significance of the event (4-point scale; 1 = *not significant*; 4 = *very significant*). For future events, participants additionally estimated the temporal distance from the present (in years) and rated the similarity of the event relative to previous experiences (4-point scale; 1 = *novel*; 4 = *identical*).

Analyses. For each participant, we calculated median response time and mean detail rating across all trials. All three time points for a given detail set were excluded from analysis if (a) no response was made during at least one of the time points, (b) response times were too fast for the participant to read the instructions on the screen (<500 ms; based on previous experiments using the same paradigm), or (c) a rating of 1 for consistency was given, indicating that participants generated distinct events across time points (see the Results and Discussion section for the proportion of trials excluded for each condition).

We analyzed our data using Bayesian order-restricted repeated-measures analyses of variance (ANOVAs) and Bayesian directional paired-samples t tests. For the ANOVAs, we used the priors defined in Rouder, Morey, Speckman, and Province (2012). For the t tests, we used a noninformative Jeffreys prior for the variance and a Cauchy prior with a width of $\sqrt{2}/2$ for the standardized effect size. For hypothesis testing, we used the Bayes factor (BF) as the statistical index, which is the ratio of the probability of the data

[1] Although past events are highly plausible, having actually occurred, we nevertheless had participants rate plausibility (i.e., how plausible each past event would have seemed a week before it happened) to equate task demands across the past and future conditions (van Mulukom, 2013). However, whether the interpretation of past and future plausibility is the same is somewhat questionable, and thus past event plausibility ratings are not discussed any further.

under one model (e.g., an alternative hypothesis) relative to the probability of the data under a competing model (often, but not necessarily, the null hypothesis). The BF hence directly compares how well competing statistical models predict the data (Wagenmakers et al., 2018). The subscript of the BF denotes which models are being compared (e.g., BF_{10} means the alternative hypothesis (1) is being compared to the null hypothesis (0), BF_{+0} means the one-sided alternative hypothesis that the effect size is positive (+) is being compared to the null hypothesis), and the value of the BF can be interpreted as how much more plausible one model is relative to the competing one (e.g., $BF_{10} = 3$ means the alternative is 3 times more probable than the null hypothesis), while $BF_{10} = 1$ means the alternative and the null hypothesis are equally probable. All statistical analyses were performed in R (RRID: SCR_001905; R Core Team, 2019), using the following packages: dplyr (Wickham, François, Henry, & Müller, 2018), tidyr (Wickham & Henry, 2018), reshape2 (Wickham, 2007), data.table (Dowle & Srinivasan, 2018), BayesFactor (Morey & Rouder, 2018), ggplot2 (Wickham, 2009), and cowplot (Wilke, 2017). Data and scripts to reproduce all analyses and figures are publicly available at osf.io/xqm5n (Wiebels et al., 2019).

Results and Discussion

Descriptive statistics for past and future events across all three time points are presented in Table 1. Response times and detail ratings for each event type are also presented in Figure 2. The analyzed data included 95.3% of all detail sets (future: M = 93.0%, SD = 6.05; past: M = 98.1%, SD = 2.63).

All other ratings data are presented in Table 2. Importantly, there was no evidence that consistency of the events across time points differed between conditions ($BF_{10} = 0.64$). Moreover, the similarity of future events to previous experiences and thoughts was low, indicating that participants imagined novel future events, as instructed.

Do novel future events take longer to construct while comprising less detail than past events? Our first prediction was that future events would take longer to construct but would nevertheless comprise less detail than past events when events are imagined/remembered for the first time in the experimental setting. To this end, we used two Bayesian directional paired-samples t tests (Morey & Rouder, 2011) between response times and detail ratings of both future and past conditions at Time Point 1. In line with our prediction, we found very strong evidence for future events taking longer to construct ($BF_{+0} = 2.81 \times 10^5$, see Figure 2B) and being less detailed ($BF_{+0} = 4.48 \times 10^7$, see Figure 2E) than past events.

These results extend previous findings (Anderson et al., 2012) by showing that it takes participants substantially longer to create a new imagined event representation than to retrieve an existing representation of a past event. Given that future events were also less detailed than past events, independently replicating previous research (e.g., Addis, Musicaro, Pan, & Schacter, 2010, Addis et al., 2009; Berntsen & Bohn, 2010; D'Argembeau & Van der Linden, 2004, 2006; Gamboz et al., 2010; McDonough & Gallo, 2010), increased response times do not reflect integration of more details, but additional cognitive demands during simulation, such as the formation of novel associations between component details.

Having confirmed that construction time and detail differences exist between past and future conditions at Time Point 1, in the next two sets of analyses, we analyzed data from all time points of the experiment to determine whether these effects reflect a fundamental difference between episodic simulation and episodic memory, or whether these differences can be ascribed to the intrinsic novelty of future events, when constructed for the first time.

Do events become faster to construct and more detailed with repetition? Our second prediction was that repetition effects would be evident for both past and future events, with a linear decrease in response times and a corresponding increase in detail ratings across time points. We computed four Bayesian repeated-measures order-restricted ANOVAs, one for each of the two conditions (past, future) and each of the two dependent variables (response times, detail ratings), with time point as the within-subject factor. Order restrictions (Haaf & Rouder, 2017; Morey & Wagenmakers, 2014; Rouder, Haaf, & Aust, 2018) allow testing more specific hypotheses than the default alternative hypothesis that all means are different, without the need for post hoc tests. The order-restricted models we used (M_1) tested for a linear decrease/increase, that is, the restriction Time Point 1 > Time Point 2 > Time Point 3 for response times and Time Point 1 < Time Point 2 < Time Point 3 for detail ratings. These models were compared to the null model of no differences between time points (M_0; Time Point 1 = Time Point 2 = Time Point 3), as well as to the unconstrained model of differences in any direction between the time points (M_u; Time Point 1 ≠ Time Point 2 ≠ Time Point 3). All models are depicted in Figure 3.

For future event response times, the order-restricted model (M_1) was preferred over all other models, showing very strong evidence not just for a difference between time points, but specifically for a linear decrease in response times across time points ($BF_{10} = 7.18 \times 10^{16}$; $BF_{1u} = 5.9$; $BF_{u0} = 1.21 \times 10^{16}$; see Figure 2A). M_1 was also the strongest model for past event response times ($BF_{10} = 9.65 \times 10^{16}$; $BF_{1u} = 5.5$, $BF_{u0} = 1.76 \times 10^{16}$). The

Table 1
Means (Standard Deviations) of Response Times and Detail Ratings From the Past and Future Conditions at Three Time Points

	Response time (ms)		Detail rating	
Time point	Past	Future	Past	Future
1	3,012.76 (850.86)	4,396.71 (1,012.97)	3.27 (0.44)	2.64 (0.33)
2	1,773.46 (804.76)	2,245.71 (958.36)	3.41 (0.38)	2.95 (0.42)
3	1,656.68 (743.60)	1,823.17 (788.09)	3.49 (0.41)	3.15 (0.49)

Note. Detail ratings made using a 4-point scale, ranging from 1 (*low*) to 4 (*high*).

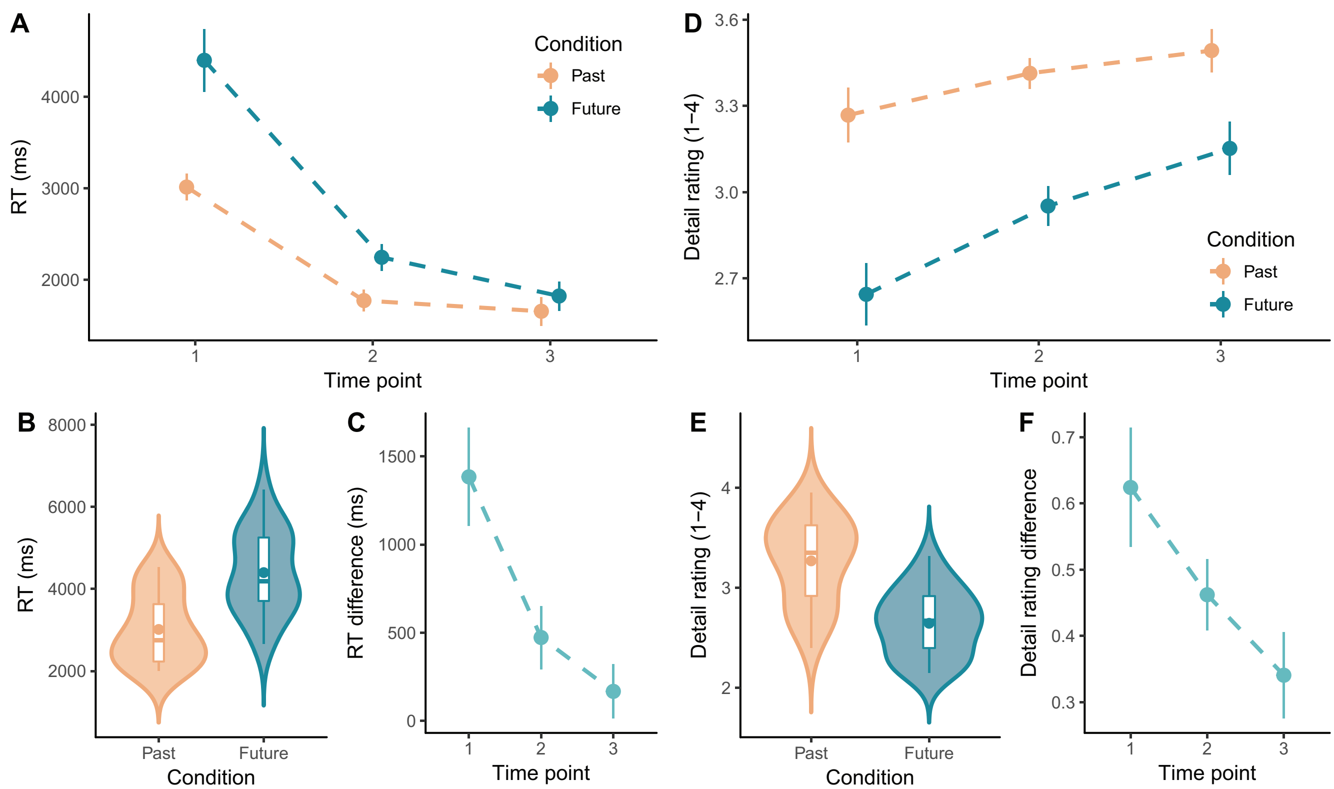

Figure 2. Future events take longer to construct (A–C) and comprise less detail (D–F) than past events, but this difference decreases across time points. (A, D) Response times (reaction time [RT])/detail ratings of past and future events at Time Points 1, 2, and 3 with 95% confidence intervals. (B, E) Initial (Time Point 1) response times/detail ratings of past and future events. The plots show the distribution of scores (violin) together with the mean (box central dot), median (box central line), first and third quartile (box edges), minimum and maximum (whiskers), and outliers (outside dots). (C, F) Difference in response times (future − past)/detail ratings (past − future) at each time point with 95% confidence intervals. See the online article for the color version of this figure.

preference for M_1 was mirrored in the detail rating analyses, which showed that detail increased linearly across time points for future ($BF_{10} = 4.96 \times 10^7$; $BF_{1u} = 6$; $BF_{u0} = 8.27 \times 10^6$; see Figure 2D) and for past events ($BF_{10} = 2{,}455.50$; $BF_{1u} = 5.6$; $BF_{u0} = 434.72$).

These results replicate previous findings indicating that response times for future event representations decrease linearly across time points, while at the same time becoming more detailed and elaborate (van Mulukom et al., 2013). We extended these findings by demonstrating that the same repetition effects are evident for past events. The remaining question now is whether this decrease differs between future and past events, that is, whether the constructive demands of future events decrease more markedly with repetition than those of past events, or whether demands change in the same way irrespective of condition.

Do future events become increasingly similar to past events across repetitions in terms of construction times and incorporated detail? The critical test of this experiment was the Condition × Time Point interaction. If repetition effects are the same for past and future conditions, then the magnitude of the past-future differences for response time and detail at the first time point will be maintained over time points. However, if repetition

Table 2
Means (Standard Deviations) of Additional Ratings From the Past and Future Conditions

Condition	Plausibility	Similarity to previous experiences	Similarity to previous thoughts	Consistency across time points	Personal significance	Temporal distance (years)
Past	2.98 (0.37)			3.47 (0.33)	2.04 (0.51)	2.56 (0.80)
Future	1.73 (0.40)	1.54 (0.36)	1.38 (0.34)	3.33 (0.34)	1.59 (0.47)	2.10 (0.56)

Note. Ratings (except temporal distance) made using a 4-point scale, ranging from 1 (*low*) to 4 (*high*). Plausibility, personal significance, and temporal distance of events were different between conditions ($BF_{10} = 5.22 \times 10^7$; $BF_{10} = 144.58$; $BF_{10} = 3.02$). Note that plausibility ratings for past events (i.e., how plausible the event would have seemed a week before it occurred) were collected to equate task demands with the future condition.

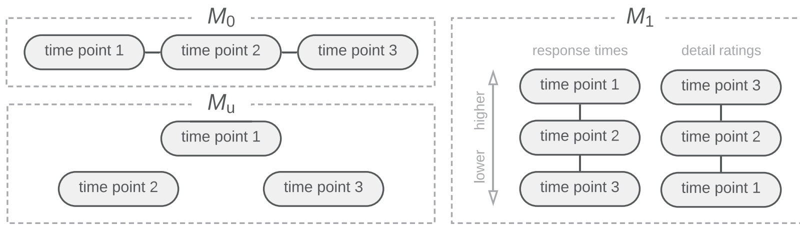

Figure 3. Models tested in Experiment 1 for response times and detail ratings of future and past conditions across the three time points. M_0: null model, Time Point 1 = Time Point 2 = Time Point 3; M_u: unconstrained model, Time Point 1 ≠ Time Point 2 ≠ Time Point 3; M_1: order-restricted model, Time Point 1 > Time Point 2 > Time Point 3 for response times and Time Point 1 < Time Point 2 < Time Point 3 for detail ratings.

effects are heightened in the future condition, then the past-future differences evident at the first time point will dissipate with repeated retrieval/simulation as future events become increasingly similar to past events in terms of response times and detail ratings. To test these alternatives, we calculated difference scores between past and future conditions, for both response times and detail ratings, at each time point. We entered each set of past-future difference scores into a Bayesian order-restricted repeated-measures ANOVA with time point as the within-subject factor (Time Point 1 > Time Point 2 > Time Point 3). We found very strong evidence that the difference between past and future event construction times decreased across time points ($BF_{10} = 2.73 \times 10^9$; $BF_{1u} = 5.9$; $BF_{u0} = 4.63 \times 10^8$; see Figure 2C). The same was the case for detail ratings ($BF_{10} = 2.59 \times 10^4$; $BF_{1u} = 5.9$; $BF_{u0} = 4{,}384.31$; see Figure 2F). These findings indicate that with repetition, future events increasingly resemble past events with regard to how fast they are constructed and how much detail is incorporated. Moreover, the results also reflect the fact that repetition effects for both response time and detail ratings were heightened in the future condition. Importantly, this pattern of findings supports the hypothesis that, relative to past events, simulating future events is particularly demanding when doing so from scratch, rather than the hypothesis that future simulation is always more demanding than retrieval.

It is important to note that the simulation of future events is unlikely to remain process-pure across repetitions, as reimagining future events at Time Points 2 and 3 will involve remembering the event as it was originally imagined at Time Point 1. With respect to interpreting the above interaction effect, retrieving the original simulation necessarily increases the similarity of the future condition with the past condition at Time Points 2 and 3. If the interaction is driven largely by the retrieval of the original simulation at Time Points 2 and 3 rather than a heightened repetition effect for future events per se, the repetition effect between Time Points 2 and 3 should be very similar for past and future events (i.e., no interaction effect). This, however, was not the case, as shown by a Bayesian directional (Time Point 2 > Time Point 3) paired *t* test on the past-future difference scores. Both construction times ($BF_{+0} = 153.64$) and detail ratings ($BF_{+0} = 89.01$) still showed a heightened repetition effect in the future compared to the past condition. Thus, while this limitation is unavoidable with this particular design, it is unlikely to solely account for the convergence of past and future events over time.

Note that although there was a slight difference in familiarity ratings of the detail sets between conditions (with future events containing more familiar components than past events), this difference is unlikely to have influenced the results as increased familiarity should have yielded effects in the opposite direction to our observed results (i.e., future events should have been associated with faster response times and more detail than past events).

Can the results be explained by other phenomenological ratings? Future events were rated as less personally significant than past events and it is thus possible that additional effort was required to align these imagined events with personal autobiographical knowledge and expectations (D'Argembeau, 2016; Klein, 2016), or to resolve potential implausibilities. In order to examine whether there was evidence for any of these hypotheses, we conducted a series of additional analyses using the personal significance and plausibility ratings. Note that these are unplanned, exploratory analyses, providing a more fine-grained description of the data.

Personal significance of events. In order to ensure that the observed past-future differences could not be explained by a difference in personal significance between conditions, we ran Bayesian repeated-measures order-restricted analyses of covariance, testing for differences in response times (future > past) and detail ratings (past > future) between future and past conditions at Time Point 1, with personal significance ratings added as a covariate. For both models, there was still very strong evidence for these differences after accounting for personal significance ratings (response times: $BF_{10} = 2.61 \times 10^5$ vs. $BF_{10} = 3.81 \times 10^5$ for the model without the covariate; detail ratings: $BF_{10} = 3.89 \times 10^6$ vs. $BF_{10} = 4.10 \times 10^7$), providing evidence against the hypothesis that the observed differences are due to past and future events differing in how personally significant they are judged to be.

Plausibility of events. Given that the interpretation of plausibility ratings is not equivalent across past and future conditions, we were unable to examine whether plausibility plays a role in past-future differences. We did, however, examine whether plausibility ratings predicted response times and detail ratings of future events on a trial-by-trial basis, using Bayesian hierarchical linear models (with random intercepts and slopes for each participant) created with the brms (Bürkner, 2017) and coda (Plummer, Best, Cowles, & Vines, 2006) R packages. We conducted two analyses, testing whether plausibility ratings predict the outcome variables during initial construction (Time Point 1), and whether they predict the respective change between Time Points 1 and 3 (see Figure 4; plots of subject-specific estimates can be found at osf.io/xqm5n). There was strong evidence that, at Time Point 1, less plausible future events took longer to construct ($b = -146.87$, 90% CI

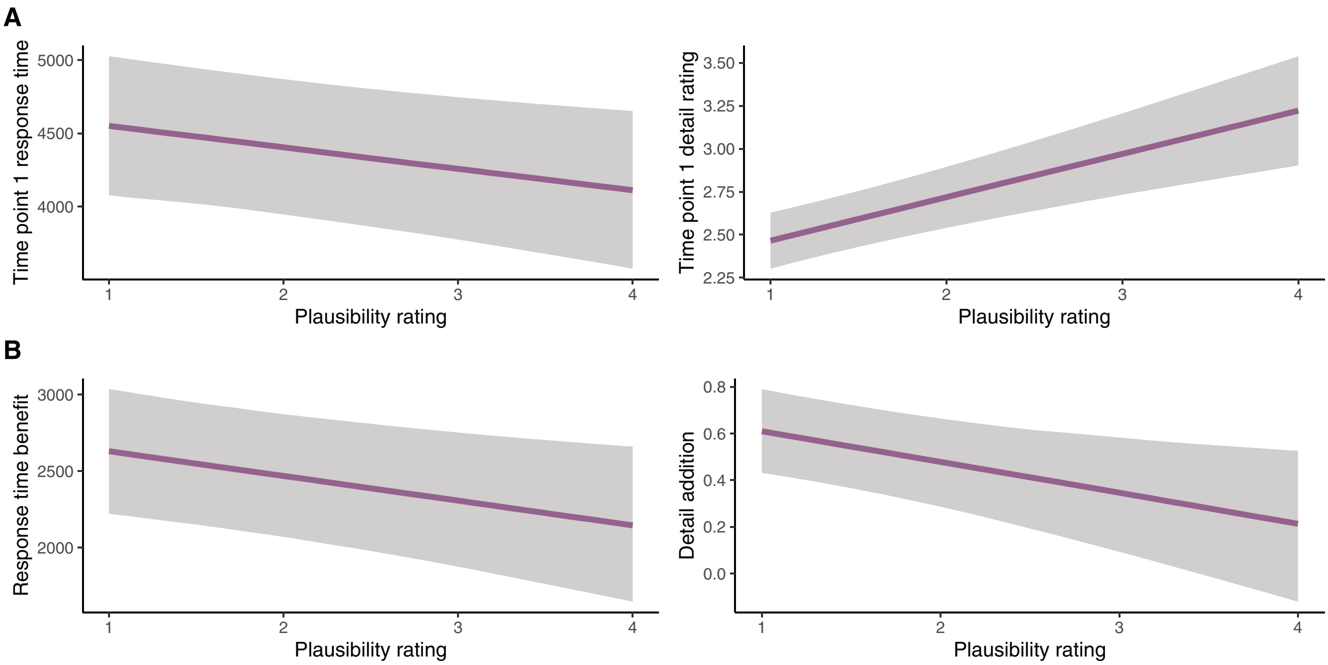

Figure 4. The relationship between future event plausibility and (A) initial construction times and incorporated detail, as well as (B) construction time and detail changes between Time Points 1 and 3. The plots show fitted models estimated via Bayesian hierarchical linear modeling, with 95% credible intervals. See the online article for the color version of this figure.

[−246.61, −45.85], BF_{-0} = 94.24) and were less detailed (b = 0.25, 90% CI [0.17, 0.33], $BF_{+0} > 5 \times 10^3$) than more plausible events. Less plausible future events also benefited more from repetition (response times: b = −160.71, 90% CI [−269.27, −49.15], BF_{-0} = 99.63; detail ratings: b = −0.13, 90% CI [−0.22, −0.05], BF_{-0} = 131.23). While our main analyses showed that the generation of novel future events imposes additional constructive demands on the simulation system as compared to remembering past events, this exploratory analysis suggests that this is especially true for future events that are less plausible with respect to one's life. As others have argued, this is likely because less plausible future events require the generation of more novel associations between disparate details (cf., Weiler, Suchan, & Daum, 2010a).

Overall, the findings from Experiment 1 demonstrate that, relative to past events, the constructive demands associated with future events are particularly heightened when these events are imagined for the first time, that is, when unique sets of details are integrated into novel representations, and even more so for implausible future events. It is likely that these amplified demands are driving many of the effects reported in the literature, as participants typically imagine future events from scratch. Although the repetition effects reported here indicate that both past and future events are constructed more quickly across time points even as the event representations become more detailed, the changes across time points are more pronounced for future events as the demands of the initial construction dissipate and past and future events become more similar. One question that follows from these findings relates to the contribution of different event components to this process—are all episodic details equally important, or do different details play different roles?

Experiment 2

Our second aim was to examine in more detail the constructive processes involved in future event simulation, by establishing the constructive demands associated with the generation of different components of these events. Specifically, we set out to clarify whether the generation of a spatial context contributes disproportionately to the construction of these events relative to other details, by manipulating directly the integration of different detail types (locations and people) into the events. Similar to Experiment 1, participants imagined future events across two time points, and we recorded response times as a proxy for construction times, as well as participants' ratings for detail, difficulty, and how similar the events were perceived to be across time points. Importantly, at Time Point 2, participants reimagined the events either exactly as at Time Point 1 (no change condition), or with a critical detail changed: either with a different person (person change condition), or in a different location (location change condition).

Given that the no change condition was identical to Time Points 1 and 2 in Experiment 1, we expected to replicate those repetition findings, namely, that relative to Time Point 1, future events at Time Point 2 would be faster to construct, but nonetheless be more detailed. We expected future event construction furthermore to become less difficult upon repetition, replicating previous research (Szpunar, St. Jacques, Robbins, Wig, & Schacter, 2014). Importantly, this condition provided us with a baseline magnitude of the effect of repetition when the event representation did not change. Additionally, we predicted that repetition effects would also be evident in the two change conditions, as participants were instructed to keep the event content constant across repetitions, apart from the one detail (person/location) that was explicitly changed. However, if a particular component detail contributes disproportionately to the construction of future event representations, then a change in that detail should reduce the magnitude of the repetition effect (i.e., the repetition-related benefit to response time and difficulty and detail ratings). Therefore, we expected that, relative to the no change condition (i.e., the baseline repetition effect), a change in key episodic details, such as person or location, should be sufficient to disrupt construction and thus reduce repetition effects. Critically, we also compared directly repetition effects in the person and location change conditions to adjudicate between two competing hypotheses: if both types of episodic details are important to event construction, in line with the constructive episodic simulation hypothesis (Roberts et al., 2018; Schacter & Addis, 2007), then the magnitude of the repetition effect for the two change conditions should be reduced to a similar degree relative to the no change condition; however, if spatial components are more critical to event construction than nonspatial components, as predicted by the scene construction and spatial scaffolding hypotheses (Hassabis & Maguire, 2007; Robin, 2018), then the location change condition should be associated with a greater reduction in repetition effects than the person change condition.

Method

Participants. Forty-four healthy young adults participated in this study and provided informed consent in a manner approved by the University of Auckland Human Participants Ethics Committee. There was no overlap of our samples between experiments. One participant was excluded because of technical problems with E-prime and one participant did not complete the experiment. Thus, data from 42 participants (9 males, Aged 18–34 years, M = 24 years, SD = 4.4 years) were analyzed.

Procedure. We adapted the paradigm from Experiment 1 in a number of ways: (a) in the stimulus collection session, we instructed participants to list 100 people and 100 locations from their autobiographical memory, rather than retrieving 100 episodic autobiographical memories (a modification to the episodic recombination paradigm used in other studies; e.g., Szpunar, Addis, & Schacter, 2012; van Mulukom, Schacter, Corballis, & Addis, 2016); (b) instead of using objects as the third detail in the detail sets, we randomly assigned a highly familiar action verb (in addition to the pseudorandom assignment of a pair of participant-generated person and location details, where detail familiarity and frequency of encounter ratings [on a 4-point scale from *once a year* to *every day*] were matched across conditions)[2]; (c) we only included two time points for each trial instead of three, as the largest change in response time and ratings data in Experiment 1 occurred between Time Points 1 and 2; (d) we only included the future condition, which was now subdivided into three conditions (no change—same detail set for Time Points 1 and 2, as in Experiment 1; person change—the person detail changed between Time Points 1 and 2, while the other two details [location, verb] remained the same; location change—the location detail changed between Time Points 1 and 2, while the other two details [person, verb] remained the same); (e) ratings following every future simulation were self-paced (rather than 4 s as in Experiment 1) and we collected difficulty ratings in addition to detail ratings (on a 4-point scale from *low* to *high*); (f) similarity ratings (operationalized in the same way as "consistency" in Experiment 1) for each set of corresponding events were collected at Time Point 2 during the experiment, rather than after the completion of all trials; and (g) ratings of event plausibility were now collected after completion of all trials in the experiment.

For each participant, people and locations from their lists were randomly combined with a list of 72 verbs to create 72 detail sets (24 in each of the 3 conditions). For detail sets in the two change conditions, a modified detail set to be shown during Time Point 2 was created by substituting the critical detail (person or location) with another of the 28 people or locations remaining on each list. Replacement details were selected pseudorandomly to match detail, familiarity, and frequency of encounter ratings as closely as possible across conditions. Additionally, the person and location details were either presented in the top or middle position of the screen in a counterbalanced fashion (while the verb was always presented last), thus half of the changed details were in the upper position and half were in the middle position.

Familiarity and frequency of encounter ratings for person and location details for each condition are presented in Table 3. Frequency of encounter ratings for locations differed between conditions (person change > location change mean, BF_{10} = 12.11; person change > no change, BF_{10} = 75.07). The other ratings did not differ between conditions (all BFs_{10} < 0.3), and there was also no evidence for a difference in the change in ratings across time points (i.e., between original and changed detail sets) between conditions (person familiarity: BF_{10} = 1.16; person frequency of encounter: BF_{10} = 0.97; location familiarity: BF_{10} = 0.02; location frequency of encounter: BF_{10} = 0.56), or for differences between the change in person familiarity/frequency of encounter and location familiarity/frequency of encounter across time points, all BFs_{10} < 0.3.

In Session 2 (about 1 to 2 weeks after Session 1; M = 9.9 days, SD = 8.1 day), each of the 72 detail sets were presented twice, resulting in 144 time points (i.e., simulation + ratings; 48 per condition; see Figure 5 for an example of two time points from one trial). The total experiment was broken into four blocks of 36 time points, after each of which participants were offered a short break. Four different pseudorandomized sequences across the 4 blocks were constructed to ensure that repetitions were always in the same block, that the distances between repetitions were distributed evenly across conditions (2–5 time points or 20–50 s, plus self-paced ratings), and that there were no more than three consecutive trials of the same condition. Participants were assigned to a version in a counterbalanced manner.

Analyses. As in Experiment 1, for each participant we calculated median response time and mean detail, difficulty, and similarity ratings. Instead of raw scores, we used difference scores to quantify repetition effects (Time Point 1 − Time Point 2 for

[2] The decision to use action verbs instead of objects was in response to feedback from participants in similar studies that, while they include the object detail in their simulations as instructed, the objects are rarely integral to the event.

Table 3
Means (Standard Deviations) of Familiarity and Frequency of Encounter Ratings for Original and Changed Details Across All Experimental Conditions

	Familiarity				Frequency of encounter			
	Person detail		Location detail		Person detail		Location detail	
Condition	Original	Changed	Original	Changed	Original	Changed	Original	Changed
No change	2.51 (0.45)		2.73 (0.51)		1.98 (0.37)		1.95 (0.38)	
Person change	2.57 (0.45)	2.48 (0.43)	2.79 (0.52)		2.03 (0.42)	1.93 (0.40)	2.09 (0.43)	
Location change	2.47 (0.35)		2.79 (0.53)	2.75 (0.52)	2.00 (0.40)		2.04 (0.38)	1.96 (0.39)

Note. Ratings were made on a 4-point scale, ranging from 1 (*low*) to 4 (*high*).

response times; Time Point 2 − Time Point 1 for ratings) for all outcome measures because our main interest lay in whether repetition effects differed across conditions. Both time points for a given detail set were excluded from analysis if response times were too fast for the participant to read the instructions on the screen (<500 ms), or if the participant indicated that they could not come up with an event (see the Results and Discussion section for the proportion of trials excluded for each condition).

Unless otherwise specified, priors for Bayesian analyses were identical to the ones used in Experiment 1, and all analyses were performed in R (RRID:SCR_001905; R Core Team, 2019), using the following packages: dplyr (Wickham et al., 2018), BayesFactor (Morey & Rouder, 2018), psych (Revelle, 2018), ggplot2 (Wickham, 2009), cowplot (Wilke, 2017), Rmisc (Hope, 2013), BEST (Kruschke & Meredith, 2018), coda (Plummer et al., 2006), and rjags (Plummer, 2016).

Results and Discussion

Descriptive statistics for future events across the three conditions are presented in Table 4. Response times, difficulty ratings, detail ratings, and similarity ratings for each event type at each time point are also presented in Figure 6. The analyzed data included 89.2% of all trial sets (no change: M = 89.98%, SD = 12.49; person change: M = 88.89%, SD = 13.55; location change: 88.79%, SD = 13.82).

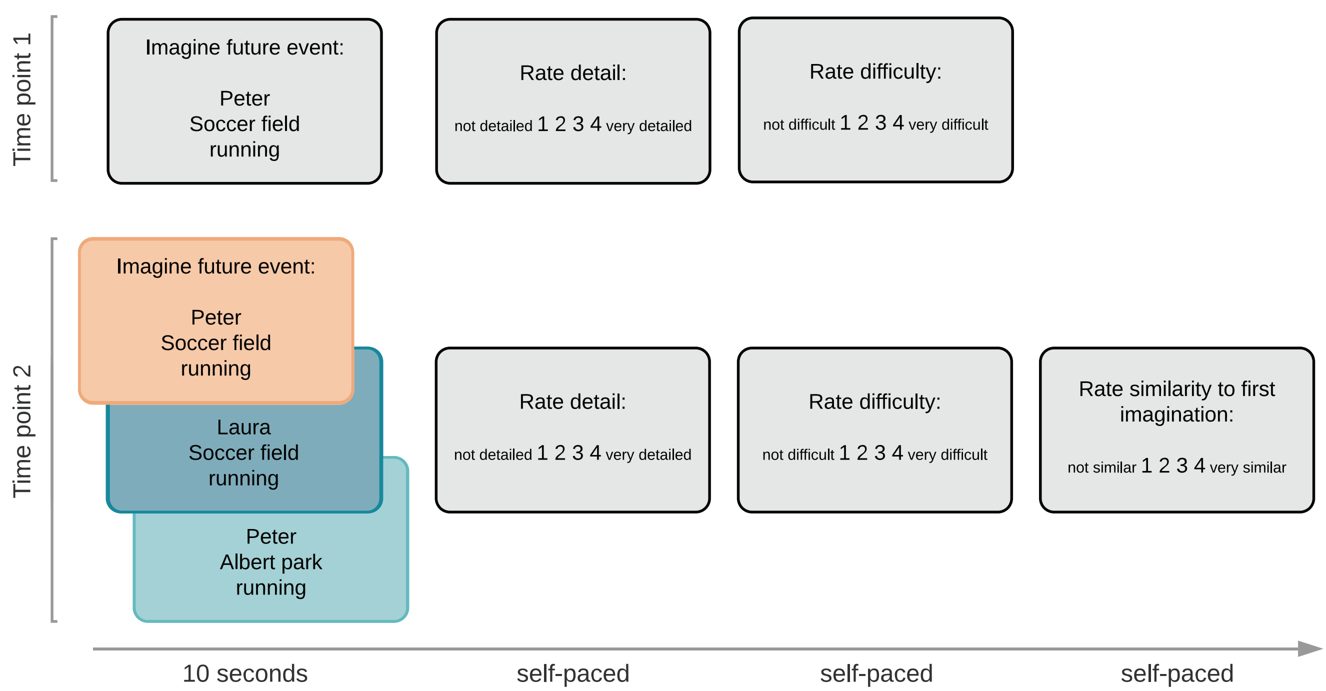

Figure 5. Corresponding Time Points 1 and 2 from an example future simulation trial in Experiment 2. At Time Point 1, participants imagined a future event involving the details presented on the screen, and at Time Point 2, they either reimagined the same event in an identical manner (no change; orange), or reimagined the event with a different person (person change; dark teal), or in a different location (location change; light teal). After simulating each event, participants rated how detailed the event was and how difficult it was to construct, and (following Time Point 2) how similar or consistent the simulations were across the two corresponding time points. See the online article for the color version of this figure.

Table 4
Means (Standard Deviations) of Response Times, and Difficulty, Detail, and Similarity Ratings Across the Three Experimental Conditions at Time Points 1 and 2

Condition	Response time (ms)		Difficulty		Detail		Similarity of events across time points
	1	2	1	2	1	2	
No change	4,780.46 (1,496.34)	2,954.40 (1,507.11)	1.91 (0.45)	1.61 (0.51)	2.93 (0.46)	2.93 (0.46)	3.65 (0.36)
Person change	4,849.92 (1,576.26)	4,093.76 (1,607.43)	1.91 (0.49)	1.93 (0.54)	2.92 (0.52)	2.85 (0.59)	2.89 (0.54)
Location change	4,830.60 (1,446.18)	4,285.90 (1,458.12)	1.90 (0.50)	1.86 (0.47)	2.94 (0.55)	2.92 (0.54)	2.65 (0.55)

Note. Ratings made using a 4-point scale, ranging from 1 (*low*) to 4 (*high*).

By design, there should be no systematic differences between conditions at Time Point 1, as the experimental manipulation was only applied at Time Point 2. To confirm this was the case, we tested for differences in response times, difficulty ratings, and detail ratings between conditions at Time Point 1 with Bayesian repeated-measures ANOVAs before the main analyses, which showed strong evidence for no differences between conditions (construction times: $BF_{01} = 9.95$; detail ratings: $BF_{01} = 11.50$; difficulty ratings: $BF_{01} = 12.66$). We also checked whether the plausibility of events differed between conditions and found strong evidence for no differences, $BF_{01} = 22.61$.

Are repetition effects evident despite changes in event components? Our first prediction was that response times and difficulty ratings would decrease, and detail ratings would increase, across time points in all three conditions. Using a series of nine Bayesian directional one-sample *t* tests (one for each dependent variable in each condition), we compared difference scores quantifying the effect of repetition against zero. In all three con-

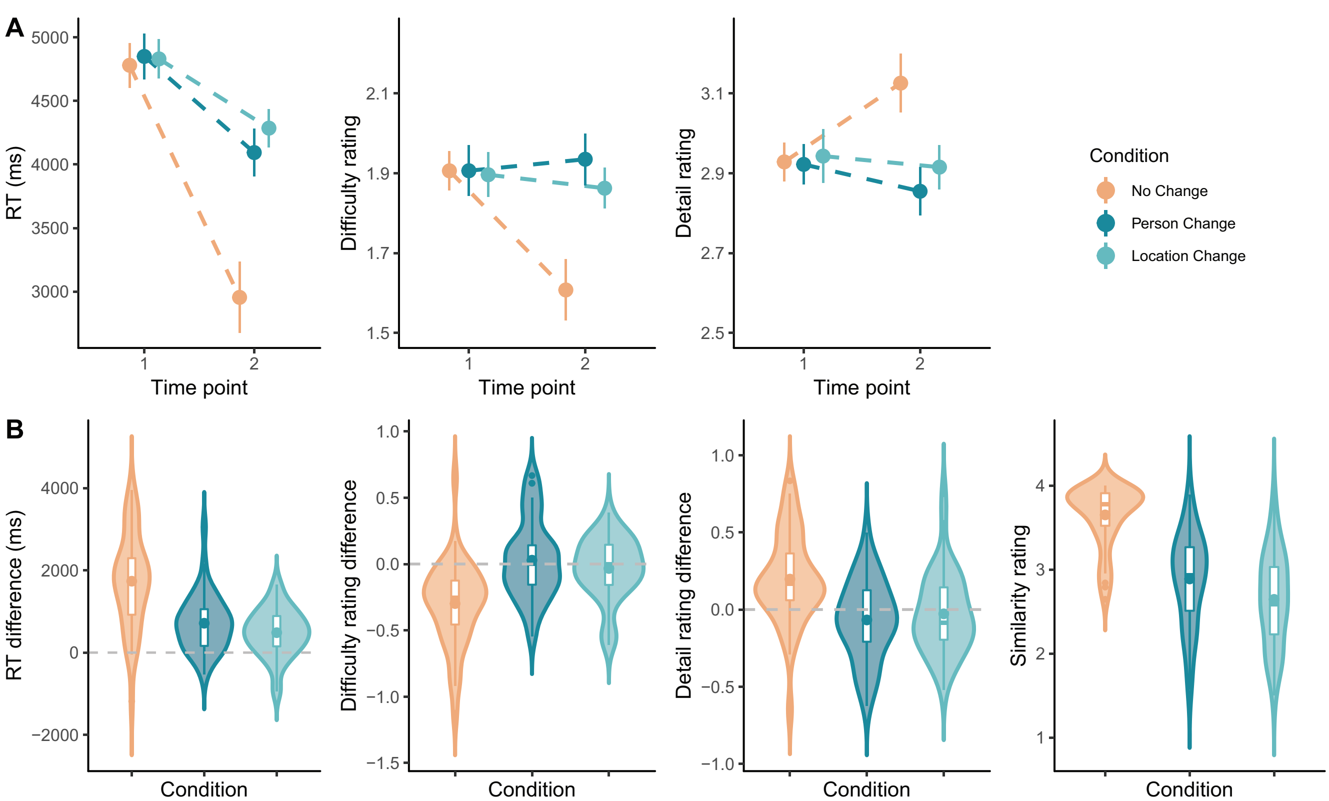

Figure 6. Response times and difficulty, detail, and similarity ratings of episodic simulations. (A) Raw response times, difficulty ratings, and detail ratings at Time Points 1 and 2 for each condition, with 95% confidence intervals. (B) Difference scores for response times, difficulty ratings, and detail ratings; and raw scores for similarity ratings (only collected at Time Point 2). The plots show the distribution of scores (violin) for each condition, together with the mean (box central dot), median (box central line), first and third quartile (box edges), minimum and maximum (whiskers), and outliers (outside dots). See the online article for the color version of this figure.

ditions, we found very strong evidence for a decrease in response time (no change: M = 1,736.42, BF_{+0} = 8.82 × 10^9; person change: M = 714.17, BF_{+0} = 7.65 × 10^5; location change: M = 484.82, BF_{+0} = 1.44 × 10^4). Moreover, in the no change condition there was also strong evidence for a decrease in difficulty ratings and an increase in the amount of detail incorporated into events across time points (difficulty: M = −0.30, BF_{-0} = 1.15 × 10^5; detail: M = 0.20, BF_{+0} = 604.81). In contrast, for both person change and location change conditions, there was stronger evidence for the null hypothesis indicating that there was no difference in difficulty and detail ratings across time points (person change: difficulty, M = 0.03; BF_{-0} = 0.11; detail, M = −0.07, BF_{+0} = 0.07; location change: difficulty, M = −0.03, BF_{-0} = 0.41; detail, M = −0.03, BF_{+0} = 0.11).

The response time findings replicate and extend the results from Experiment 1, demonstrating that repetition facilitates faster construction of imagined future events, even when there are specific alterations in content. Despite faster response times overall, changes in person and location details disrupted the effects of repetition on the subjective difficulty of event construction and the amount of detail imagined. While reimagining future events in exactly the same way was perceived as less difficult and resulted in the generation of more detailed representations, the alteration of one detail—irrespective of detail type—eliminated these repetition effects.

Do changes to spatial context differentially reduce repetition effects? Beyond examining whether repetition effects are generally evident even when one key component has changed, the main goal of this experiment was to compare directly the impact of changes in spatial and nonspatial details to determine whether these detail types have a differential influence on future event construction. We predicted that reimagining events without any changes would lead to a greater repetition effect than in the two change conditions. Critically, if spatial components are more central to the construction of future events, we predicted that a location change should result in a greater reduction of repetition effects than a person change. In contrast, if both types of episodic details are important to event construction, then location and person changes should reduce repetition effects to a similar degree. To test these predictions, we entered each dependent variable (difference scores for response times, difficulty ratings, and detail ratings, as well as Time Point 2 ratings for event similarity) into four separate Bayesian one-way order-restricted repeated-measures ANOVAs, where each ANOVA compared four models with different order and equality constraints (Figure 7, top). We constructed these models in a way such that the no change condition—as the baseline condition—always had the greatest repetition

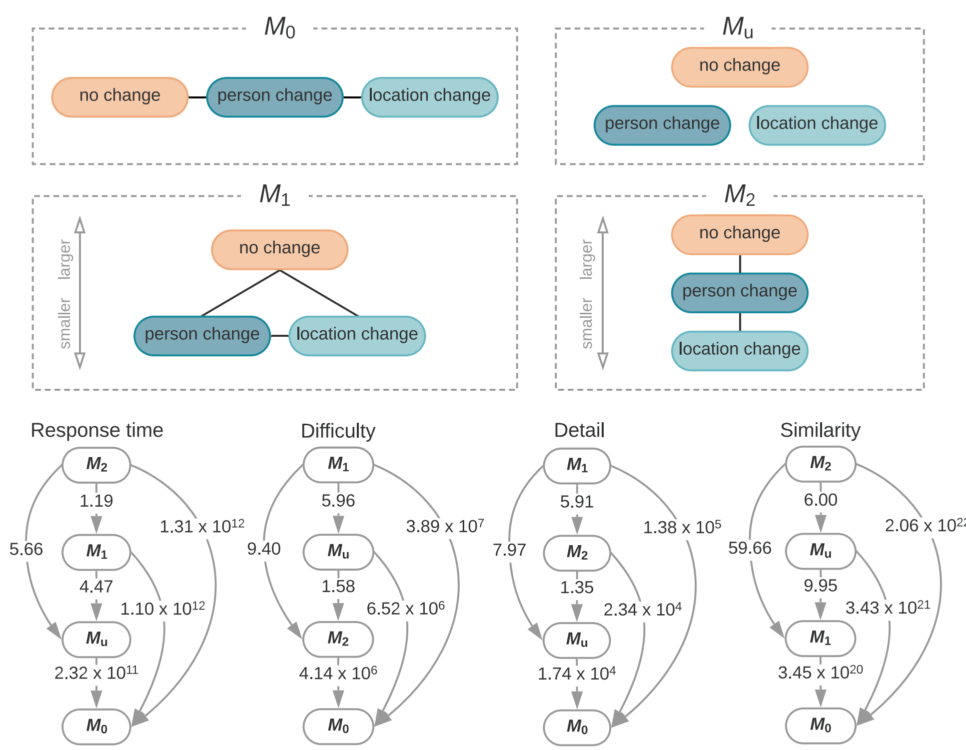

Figure 7. Upper panel: Repetition effects models tested in Experiment 2 (top). M_0: null model, no change = person change = location change; M_u: unconstrained model, no change ≠ person change ≠ location change; M_1: order and equality restricted model, no change > (person change = location change); M_2: order-restricted model, no change > person change > location change. Lower panel: Results for response times, difficulty ratings, detail ratings, and similarity ratings. Diagrams show the models from strongest (top) to weakest (bottom) and the Bayes factors between each pair of models. See the online article for the color version of this figure.

effects, while being able to simultaneously test whether a location change was associated with greater (M_2; no change > person change > location change), or the same (M_1; no change > [person change = location change]) degree of repetition-related reduction as a person change. We compared these models against both an unconstrained model (M_u; no change ≠ person change ≠ location change), which holds that there are differences between conditions without specifying the directions, and the null model (M_0; no change = person change = location change) that there is no difference between conditions. The critical comparison was thus between M_1 and M_2.

For response time data, M_2 was the preferred model, 1.2 times stronger than M_1, 5.7 times stronger than the unconstrained model (M_u), and 10^{12} times stronger than the null model (M_0; see Figure 7 for BFs between all models for each dependent variable). Although M_2 models the location change condition as having smaller repetition effects than the person change condition, in line with the hypothesis that spatial context plays a more important role in the construction of future events than nonspatial details, it is important to note that the evidence for supporting M_2 over M_1 was very weak; at only 1.2, the BF indicates that M_2 is only slightly more probable than M_1 (i.e., if BF = 1, M_2 and M_1 would be considered equally probable). We elaborate further on this point in the section below.

With respect to both difficulty and detail ratings, M_1 was the strongest model (difficulty: $BF_{1u} = 6$, $BF_{12} = 9.4$, $BF_{10} = 10^7$; detail: $BF_{12} = 5.9$, $BF_{1u} = 8$, $BF_{10} = 10^5$). These results suggest that, while repetition effects for the difficulty and detail ratings were smaller during both change conditions relative to the no change condition, there was no difference between person and location changes in the magnitude of decrease from Time Point 1 to Time Point 2. Finally, M_2 was the preferred model for the event similarity ratings collected at Time Point 2 ($BF_{2u} = 6$, $BF_{21} = 59.7$, $BF_{20} = 10^{22}$). This finding indicates that, while the future events constructed at Time Points 1 and 2 in the no change condition were rated as more similar than when a key detail changed between time points, altering the location in particular made the events subjectively less similar than altering the person.

Follow-up analyses for response time repetition effects in the two change conditions. As aforementioned, the BF of our critical comparison of M_2 over M_1 for response time was very weak. It is possible, however, that the large difference between the no change condition and the two change conditions (which was included in both models) inflated the similarity of models M_1 and M_2 at the expense of smaller differences. In other words, the no change > change condition effect may have obscured a potentially larger difference between person change and location change conditions. To explore this possibility, we focused exclusively on the two change conditions, and used a Bayesian directional paired *t* test to test whether repetition effects are smaller following a change in location versus a change in person. We complemented this analysis with Bayesian parameter estimation, which, rather than contrasting models, allows for estimation of the magnitude of parameters of interest, as well as their uncertainty, both of which are derived from the posterior probability distribution. Importantly, it also assesses the range of the most credible parameter values, and whether this range includes the null (i.e., 0). Put another way, it assesses whether or not parameter values around zero are among the most credible values of the parameter. We followed the procedure outlined by Kruschke (2013, 2018) by constructing a 95% highest density interval (HDI),[3] that is, the interval of the posterior probability distribution that includes 95% of the most credible values. We calculated the difference of repetition effects between conditions (person change repetition effects−location change repetition effects) to determine whether the difference between conditions is nonzero, and used a *t* distribution[4] as descriptive model of these data—thus estimating mean μ, standard deviation σ, and normality parameter ν—with hyperparameters defined as follows: $\mu \sim N(y, s_y 10^3)$; $\sigma \sim U(S_y/10^3, S_y 10^3)$; $\nu \sim \lambda(1/29) + 1$, with $\nu \geq 1$. Markov chain Monte Carlo (MCMC) with three chains, each with 10^6 iterations (no thinning) and a burn-in of 10^3, was used to generate posterior samples. MCMC chains were checked for convergence and to ensure that they were of sufficient length (for all parameters, $\hat{R} = 1$ and ESS (effective sample size) >10,000).

The Bayesian directional paired *t* test showed evidence for a difference between the two conditions ($BF_{+0} = 3.84$). Even though this Bayes factor does not constitute strong evidence, this result was further supported by our Bayesian parameter estimation. The marginal posterior distributions on the three estimated parameters (μ, σ, and ν), the posterior distribution on the effect size (μ/σ), and a posterior predictive check are shown in Figure 8. The posterior distribution for μ had a mean of 233.48 (*SD* = 97.91), indicating that when spatial context changed, response time repetition effects were reduced by about 233 ms relative to person changes. Importantly, all of the credible values of μ were nonzero (95% HDI: [38.98, 425.36]). The posterior distribution on the effect size also indicated a nonzero difference between conditions (*M* = 0.40, *SD* = 0.18; 95% HDI: [0.05, 0.74]). The posterior predictive check (Figure 8B), which was created by plotting the *t* distribution of randomly selected steps in the MCMC chains together with a histogram of our data, suggested that the *t* distribution was a good description of our data.

Taken together, these results suggest that spatial context contributed to the time it takes to construct future events more than person details, in line with theories highlighting the central contribution of space in episodic simulation (e.g., scene construction theory: Hassabis & Maguire, 2007; spatial scaffold effect: Robin, 2018). Moreover, events that differed only with respect to spatial context were perceived as less similar than events that differed only in person, further supporting the notion that spatial context constitutes a defining feature of the event. Importantly, these effects cannot be ascribed to a difference in familiarity or plausibility ratings of people and locations between the two conditions (see Table 3). Although there was a difference between conditions in location frequency of encounter ratings, this difference is unlikely to have influenced the reported effects given that it was very small (0.08 on a 4-point scale) and that the change in this rating between time points did not differ between conditions. It could also be argued that some activities, as determined by the verbs that were part of the detail sets, were more easily imaginable in some locations than in others. If true, this would mean that location

[3] Although the HDI is similar to a frequentist confidence interval in that it reflects the uncertainty of the estimated parameter value, there are important differences in that an HDI also provides information regarding the probability of the parameter value, given the data (Kruschke & Liddell, 2018).

[4] Note that the use of a *t* distribution allows more flexibility than a Gaussian distribution, especially as it can better accommodate extreme data points.

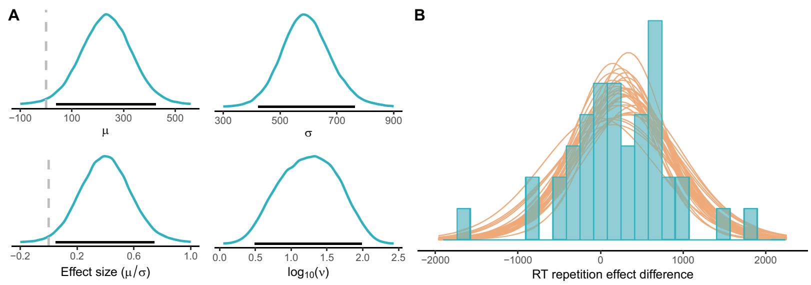

Figure 8. Parameter estimation of the difference in response time repetition effects (person change − location change) against zero. Results further support the model comparison analysis result that repetition effects are smaller in the location change condition than in the person change condition. (A) Posterior distributions on the mean (μ), standard deviation (σ), effect size (μ/σ), and the normality parameter ($\log_{10}\nu$). On each distribution, the 95% HDI is marked (black line). Gray dashed line indicates a difference/effect size of zero. (B) Posterior predictive check, consisting of a histogram of the data and a random selection of 30 credible *t* distributions from the Markov chain Monte Carlo samples. See the online article for the color version of this figure.

changes were more disruptive than person changes, simply because of incongruencies between certain types of actions and specific locations. In order to circumvent this potential confound, our design only included verbs describing activities that are plausible regardless of spatial context (e.g., jumping, singing, laughing).

The pattern of results described above did not hold for incorporated detail and perceived construction difficulty. The fact that incorporated detail did not differ between the two change conditions is perhaps not surprising, given that in both of these conditions only one key detail was changed and replaced with another detail that should be similarly detailed. However, the results for perceived difficulty went against our prediction; we expected them to be in line with the construction time findings. This could potentially be an artifact of our design; the activity that was part of the event did not have to be, but typically was (according to descriptions by our participants) carried out by the provided person in the event. Thus, it is possible that when the person was changed, participants found it more difficult to imagine a different person doing the same action, inflating the difficulty ratings for that condition.

General Discussion

In this series of experiments, we examined the construction process of past and future events. First, we tested whether it is always more demanding to imagine future events than to recall past events, or whether the increased demands with future simulation are particularly heightened when imagining events from scratch. The results of our first experiment suggest the latter to be the case; when initially imagined, future events took substantially longer to construct despite being less detailed than past events, but with repetition, future events and past events became increasingly similar. We also investigated whether these amplified demands are driven by specific event components. The second experiment provided evidence for this hypothesis, such that the construction of a spatial context influenced construction times and perceived similarity of events more than person details. Subjective difficulty to construct the event and incorporated detail, however, were not influenced by event component type. These results, being the first to investigate specifically the construction process of past and future events and their components, offer new insights with implications for current theoretical frameworks of episodic memory and episodic simulation.

Our results dovetail with previously reported differences between episodic memory and episodic simulation (e.g., past events being more detailed, more specific, and easier and faster to generate than future events). However, our findings also suggest that the interpretation of these results as past-future differences might be misguided; instead of reflecting temporal orientation, they might be attributable to the nature of the experimental paradigms and tasks typically used in these studies. In our experiment, once future events had been created and reimagined repeatedly, differences in construction time and generated detail between past and future events dissipated. This effect had not been evident before this study, because experiments have not considered how the construction of past and future events changes across repeated simulations.

This finding corroborates theoretical and empirical work highlighting the high degree of similarity between episodic memory and episodic simulation (e.g., Addis, 2018; Buckner & Carroll, 2007; D'Argembeau & Van der Linden, 2004; Ingvar, 1985; McDermott & Gilmore, 2015; Schacter & Addis, 2007; Spreng, Mar, & Kim, 2009; Suddendorf & Corballis, 2007; Tulving, 1985), consistent with the view that episodic memory and episodic simulation are instantiations of one simulation system or a general faculty of mental time travel, as well as with philosophical positions of continuism, which argue that—apart from temporal orientation—there is no fundamental difference between episodic memory and episodic simulation (e.g., Perrin & Michaelian, 2017). In line with this, Addis (2018) suggests a reconceptualization of past-future differences as differences in "associative history" (i.e., how often the details comprising the event have been temporally coactivated). According to this account, the fluency of the event increases—and constructive demands decrease—the more often an event representation is retrieved and the stronger associations between event components become (up to a certain point, after which these changes level out). Our results provide direct evidence for this account, with event construction being slow and demanding when event components have not been associated before (i.e., future events at Time Point 1), events being brought to mind with increasing ease as the associative strength of the event representation increases (i.e., past and future events across Time Points 1 to 3), and the magnitude of this repetition effect decreasing across time points (i.e., difference between past and future events across Time Points 1 to 3). A similar effect has been reported for novel counterfactual simulations (simulations of alternative ways past events could have occurred, i.e., past events that are created from scratch), which, when imagined repeatedly, became more detailed and easier to generate (De Brigard, Szpunar, & Schacter, 2013), further supporting the view that these effects reflect associative strength of event representations, rather than temporal orientation. According to the constructive episodic simulation hypothesis, a likely underlying mechanism for constructive demands that change as a function of associative history is the degree of relational processing required to integrate all components into the event representation, which is high for novel combinations, and decreases as associations become stronger. Interestingly, in other studies we have found that when the components comprising novel future events are disparate, construction times and perceived difficulty are higher still—and incorporated detail lower—compared to novel future events including related components (Roberts et al., 2017; van Mulukom et al., 2016). Our exploratory analyses in Study 1, showing that constructive demands are modulated by plausibility, such that less plausible events are less detailed but take longer to imagine, provide further evidence for this idea.

An account focused on relational processing could also explain the findings of our second experiment, which demonstrated that the heightened constructive demands when future events are imagined from scratch—especially the time it takes to construct the events—are driven, in large part, by spatial context. These results are broadly consistent with theories highlighting the central role of spatial processing in episodic simulation (e.g., scene construction theory: Hassabis & Maguire, 2007; spatial scaffold effect: Robin, 2018) and could reflect a fundamental difference between the role different event components play during the construction process. Indeed, spatial context has been argued to provide the stage upon which the event plays out (Hassabis & Maguire, 2007; see also Rubin, Deffler, & Umanath, 2019), and is thus critical to any event representation. However, an alternative explanation is that the difference lies more generally in the degree of relational processing required to construct different event components. If each event component comprising an event is, in and of itself, an assemblage of relevant semantic, episodic, and other sensory elements, then more elaborate representations would have a greater influence on event construction times (for a discussion of this point, see Roberts et al., 2018). Findings from studies using the scene construction task indicate that scene representations do contain more than spatial elements, including episodic content such as entities, sensory descriptions, thoughts, emotions, and actions (Hassabis & Maguire, 2007; Madore, Jing, & Schacter, 2019). Thus, it is possible that spatial contexts are more elaborate than other event components (e.g., people, objects), and result in more intensive relational processing at the level of event components, instead of events per se. This hypothesis is consistent with our results, though it remains to be tested directly: for example, via the manipulation of the number of elements that make up event components (such as people and spatial context).

A related point concerns the categorical distinction between spatial and nonspatial event components, instantiated in the present study via the contrast between spatial contexts and person details. This distinction is nontrivial; it could be argued that person details are also spatial, in the sense that they have a position in space, and that they themselves are made of spatial elements—in contrast to event components such as actions or emotions (for a broader discussion, see also Ekstrom & Ranganath, 2018). Another outstanding question, and a potential avenue for future research, is thus whether our results extend to event components that truly lack any spatial elements.

In conclusion, we have shown that constructive demands are heightened when events are imagined from scratch—as is the case with novel future events—and that construction times and incorporated detail of future events become increasingly similar to past events when repeatedly constructed. These findings suggest that constructive demands may reflect differences in associative strength, rather than fundamental differences between episodic memory and episodic simulation. Furthermore, we have shown that aspects of the constructive process, particularly construction times, are influenced disproportionately by spatial context compared to person details. While this could be due to spatial context playing a more central role in event construction, it could also be that spatial contexts are simply more elaborate in nature, consisting of more elements that have to be bound together by relational processing. If confirmed by future research, this interpretation could bridge theoretical accounts focused on explaining different aspects of event construction. A promising way forward might be to reframe theoretical accounts that are based on categorical distinctions into more continuous frameworks (Dalton, Zeidman, McCormick, & Maguire, 2017; Eichenbaum & Cohen, 2014; Roberts et al., 2018).

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