No evidence for short-timescale temporal declines in expectations within a controlled cognitive task

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Abstract

People waiting to receive information about a personally relevant future event often become increasingly pessimistic as the event draws near. These temporal declines in expectations have been demonstrated robustly across both naturalistic and laboratory settings. However, the low-level cognitive processes that give rise to temporal declines in expectations remain unclear. Here, we investigated the temporal boundary conditions of this effect. In a controlled cognitive task involving repeated probabilistic gambles, we assessed the dynamics of participants' reward expectations over a 12-second waiting period prior to revelation of the gamble outcome. Across two experiments (total N = 120), we found no evidence for temporal declines in expectations over this short waiting period, no matter whether expectations were measured via direct probability report (Experiment 1) or via an incentive-compatible 'cash-out' decision (Experiment 2). These results demonstrate that temporal declines in expectations are not an invariant characteristic of human expectations regarding personally relevant future events.

Keywords: expectations; waiting; uncertainty; optimism; pessimism; decision making

Introduction

In everyday life, we frequently encounter situations in which we must wait in uncertainty before learning the outcome of a personally relevant event. Individuals in these situations—such as a patient waiting to find out the result of a medical test, or a student waiting to learn whether they have passed an exam—are confronted with a dilemma: what expectations should they hold while they are waiting? On the one hand, optimistic expectations are thought to produce greater psychological wellbeing during the waiting period (S. E. Taylor & Brown, 1988); on the other hand, increased optimism also increases one's risk of disappointment when the event occurs (Van Dijk, Zeelenberg, & Van der Pligt, 2003; Sweeny & Shepperd, 2010). In fact, previous research suggests that individuals adopt a trade-off between these factors in the form of *temporal declines in expectations* (Shepperd, Ouellette, & Fernandez, 1996; Carroll, Sweeny, & Shepperd, 2006). That is, expectations regarding the outcome of an uncertain future event tend to decline as the event approaches in time, from initial optimism when the event is distant in time to 'defensive pessimism' (Norem & Cantor, 1986) as the event approaches (see Sweeny & Krizan, 2013 for review).

A number of theories have been posited to explain temporal declines in expectations, including affect management, shifts in construal level, and shifting accountability pressures (see Sweeny & Krizan, 2013 for review). From the perspective of cognitive science, however, a fundamental question that remains unclear is whether declining expectations are a general feature of expectations during a waiting period, or whether they occur only under specific conditions (as suggested by, e.g., construal-level theory; Trope & Liberman, 2003).

In this light, a crucial question is whether expectations decline even across very short wait durations (on the order of seconds). One meta-analysis suggested that longer delays (on the order of days/weeks) tend to produce larger expectation declines overall (Sweeny & Krizan, 2013); however, declines in expectations have also been reported over delays as short as 20 to 30 minutes (Terry & Shepperd, 2004; Van Dijk et al., 2003). To our knowledge, however, no previous study has assessed the boundary conditions of the effect by measuring the dynamics of expectations over very short timescales.

Why might we expect expectations to decline even over short wait durations? One possibility is that temporal declines in expectations can be understood as a form of intrinsically motivated belief updating (cf. Kappes & Sharot, 2019). If so, it is conceivable that expectations might decline even over short timescales, since it has been shown that belief updating in response to *external* prompts can occur rapidly (i.e., over several seconds; Vossel, Mathys, Stephan, & Friston, 2015; Bennett, Murawski, & Bode, 2015).

More broadly, if temporal declines are a property of expectations in general—even over short timescales—this would have important implications for understanding behavior in any task involving a pre-outcome waiting period. For instance, short-timescale declines in expectations might help to understand individuals' preferences for stimuli that allow them to avoid waiting in uncertainty (Bennett, Bode, Brydevall, Warren, & Murawski, 2016; Tanovic, Hajcak, & Joormann, 2018; Embrey, Liew, Navarro, & Newell, 2020), as well as neuroimaging studies of brain activation in anticipation of future reward/punishment (e.g., Oldham et al., 2018).

In the present study, we investigated whether participants' expectations regarding a valenced future outcome would decline during a 12-second waiting period prior to the receipt of outcome information. Specifically, across two experiments we used a novel cognitive task to assess participants' subjective beliefs regarding the likelihood of receiving a reward outcome in an upcoming probabilistic gamble, while manipulating both the risk and the ambiguity of the gamble.

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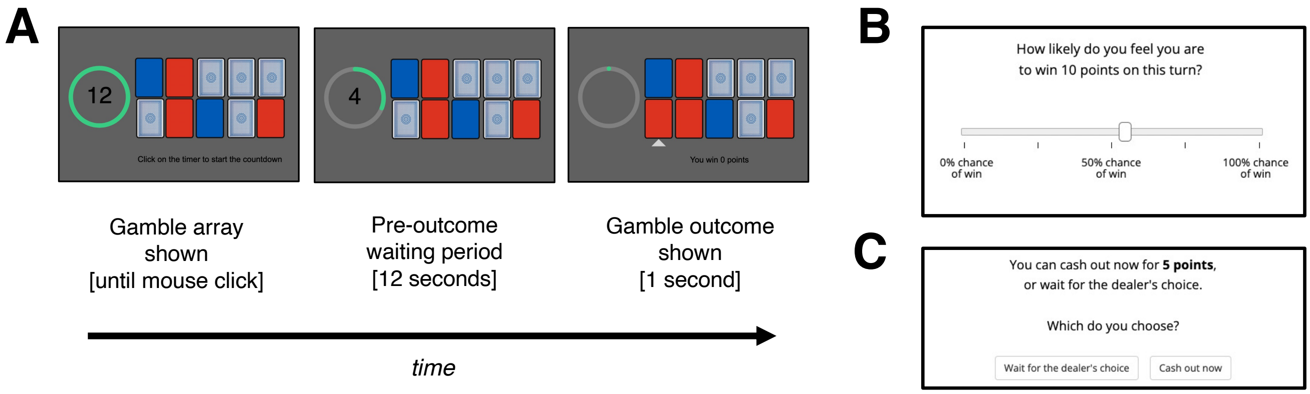

Figure 1: Overview of cognitive task. **A**: Each gamble was presented as an array of ten face-up and face-down cards. Participants clicked on the circular green timer to initiate a 12-second waiting period; at the end of this period, one card was selected at random (selection indicated by a white triangle; the selection was made randomly by a fictitious 'dealer', according to the experiment cover story) and participants were awarded the associated point amount. In this example, blue cards are worth 10 points are red cards are worth 0 points. **B**: Once per waiting period, we elicited participants' beliefs regarding the probability of winning the gamble. In Experiment 1, beliefs were directly reported via probability slider. **C**: In Experiment 2, beliefs were elicited via an incentive-compatible 'cash-out' choice option.

Experiment 1

Method

Participants 60 participants (27 female, 29 male, 4 who did not endorse a binary gender) were recruited via the website Prolific to complete an online cognitive task. Participants were aged between 18 and 61 years (mean age 27, SD = 11.16) and resided in Australia, Canada, Ireland, New Zealand, the UK, or the USA. Participants were paid \$4 for participation, plus a bonus up to \$2 depending on task outcomes (mean bonus = \$0.90, SD = 0.13). All participants provided informed consent, and this study received ethical approval from the Human Research Ethics Committee of Monash University (project ID: 29596).

Cognitive task In each trial of the cognitive task, participants were presented with an ambiguous probabilistic gamble in the form of an array of ten red and blue cards (see Figure 1A). Participants clicked on a 'countdown timer' to begin a 12-second waiting period, after which one card was selected at random, and the participant won a number of points that depended on the color of the selected card. Outcomes were either a 'win' (gain of 10 points) or a 'loss' (0 points), with mapping between card color and win/loss outcome randomized across participants. After the task, trial outcomes were translated into a monetary bonus at a rate of \$1 per 300 points.

Once per trial, participants were asked during the waiting period to report using a probability slider how likely they felt it was that they would win 10 points at the end of the waiting period (Figure 1B). To estimate the temporal profile of participants' expectations, the belief-report time was varied across trials, such that probability reports could occur at 12, 9, 6, 4, 2, 1, or 0 seconds prior to outcome revelation.

Each gamble array comprised a mix of face-up and face-down cards. The face color of face-down cards was not visible to participants unless that card was selected at the end of the waiting period, at which point the card was turned over to reveal its face color. This manipulation was designed to add ambiguity to the probability estimation procedure, since we reasoned that probabilities with a degree of ambiguity might be more subject to temporal declines in expectations than unambiguous probabilities (e.g., an array of only face-up cards, in which participants might easily calculate the true win probability). Participants were informed that face-down cards were drawn from a deck in which there was an equal number of red and blue cards. This was designed to ensure that participants understood that face-down cards could be either red or blue, independent of the color composition of the face-up cards (cf. Bennett et al., 2017). To test the effect of ambiguity on temporal declines in expectations, trials belonged to either a low-ambiguity condition (1 of 10 cards face-down) or a high-ambiguity condition (5 of 10 face-down).

Within each ambiguity condition, there were four prior win probabilities, (each corresponding to a different array of red/blue cards): 25%, 45%, 55%, or 75%. Each participant completed a total of 56 trials (4 probabilities $\times$ 2 ambiguity conditions $\times$ 7 belief-report times). Trial order and visual configuration of cards for each gamble type were randomized. Following instructions, participants were required to answer several comprehension check questions correctly before proceeding to the task. Task duration was approximately 25 minutes, and the task was presented in participants' web browsers using a combination of JavaScript (`jsPsych` library; De Leeuw, 2015) and custom-written Python server code.

Data exclusions To identify inattentive participants, eight attention checks were randomly interspersed throughout the task. These checks appeared during the inter-trial interval, and asked participants to report how many points they had won on the most recent trial. 9 participants (15% of sample) responded incorrectly to one or more attention check, and were excluded from all further analysis. Data from one additional participant failed to save due to server error.

To ensure that participants maintained attention to the gamble throughout the entire waiting period, we also monitored browser interactions and excluded any trial in which a participant clicked away from the browser during the waiting period (174 trials excluded, 6.2% of total).

Data analysis Data were analyzed using a Bayesian mixed-effects regression analysis as implemented in the `brms` package for R (version 2.16.3; Bürkner, 2017). This model used a maximal random-effects structure, with random intercepts for participants and random slopes for all within-participants main effects and interactions (Barr, Levy, Scheepers, & Tily, 2013). Continuous predictors were grand-mean-centered prior to analysis, and ambiguity was analyzed using treatment coding, with low ambiguity as the reference condition. All probabilities were expressed as percentages.

Models were fit with four independent chains of 4000 iterations each, with the first 1000 samples from each chain discarded to prevent dependence on random initial values. We retained the default prior specifications suggested by `brms`. Population coefficient estimates were treated as credibly different from zero if the 95% Bayesian Highest Density Interval [HDI] excluded zero. All data for this study are openly available at `https://osf.io/4r5p9/`.

Results

Manipulation check We first examined the correspondence between participants' reported win probabilities and the true win probability for each gamble. We found a close correspondence between reported and true win probabilities (Figure 2A), giving us confidence that participants accurately understood the task and the probability-reporting instructions.

Regression analysis In line with the correspondence between true and reported probabilities presented in Figure 2A, the Bayesian mixed-effects regression analysis revealed a credible effect of true win probability on participants' reported win probability ($\beta = 1.03$, 95% HDI $[0.90, 1.16]$). True win probability also interacted with ambiguity ($\beta = -0.23$, 95% HDI $[-0.35, -0.10]$), such that participants adjusted their probability reports more conservatively under high ambiguity than under low ambiguity condition (Figure 2A). There was no evidence for a main effect of ambiguity on reported win probabilities ($\beta = -0.73$, 95% HDI $[-2.00, 0.54]$).

Contrary to the temporal-decline hypothesis, we did not find any evidence that reported win probability declined as the moment of outcome revelation approached ($\beta = -0.09$, 95% HDI $[-0.29, 0.11]$). This indicates that, on average, reported win probabilities remained relatively flat over the delay period prior to revelation of the gamble outcome (see Figure 2B). This flat profile of reported expectations also did not interact significantly with the true win probability of the gamble ($\beta = -0.01$, 95% HDI $[-0.02, 0.0002]$; see Figure 2C), or with ambiguity level ($\beta = 0.05$, 95% HDI $[-0.21, 0.35]$), and there was also no credible evidence for a three-way interaction ($\beta = 0.01$, 95% HDI $[-0.003, 0.03]$).

Quantifying support for a null model The regression analysis reported above found no credible effect of time until outcome on reported win probabilities. However, an apparent null effect of time until outcome does not necessarily support the null hypothesis; this result might also arise if the statistical power of Experiment 1 was not sufficient to distinguish between the null hypothesis and the alternative hypothesis (Aczel et al., 2018). For this reason, we next conducted an auxiliary analysis to directly compare support for a full mixed-effects regression model including main effects and interactions of time until outcome, relative to a reduced mixed-effects regression model in which these effects and interactions were not included. We compared models using the framework of Bayesian Model Averaging (BMA; see, e.g., Hinne, Gronau, van den Bergh, & Wagenmakers, 2020), which quantifies the posterior probability of different models conditional on the observed data. This provides a measure of the strength of evidence in favour of each model normalized between 0 and 1. We estimated posterior model probabilties using pseudo-BMA with 10,000 Bayesian bootstrap samples (Yao, Vehtari, Simpson, & Gelman, 2018). Results indicated that the posterior probability of the null model was far higher than that of the full model including effects of time until outcome (estimated posterior probability of 0.94 for the null model, versus 0.06 for the full model).

Interim Discussion

Experiment 1 used a novel cognitive task to test the prediction that participants' expectations regarding the outcome of a gamble would decline over the course of a short waiting period. Contrary to this hypothesis, we found no evidence for any change in participants' expectations over the course of the waiting period: the temporal profile of expectations was flat, with no evident increases or declines. We also found no evidence that the temporal profile of expectations differed as a function of either prior probability of a win or the ambiguity of the gamble, though we did find that participants' self-reported beliefs tracked true win probabilities more closely under low ambiguity than under high ambiguity.

One notable feature of Experiment 1 is that beliefs were elicited by means of direct probability report. Direct belief elicitation is common in the literature on temporal declines in expectations (Sweeny & Krizan, 2013); however, there are two potential disadvantages of this approach that may have affected our capacity to detect temporal declines in expectations in Experiment 1. First, although gamble outcomes were

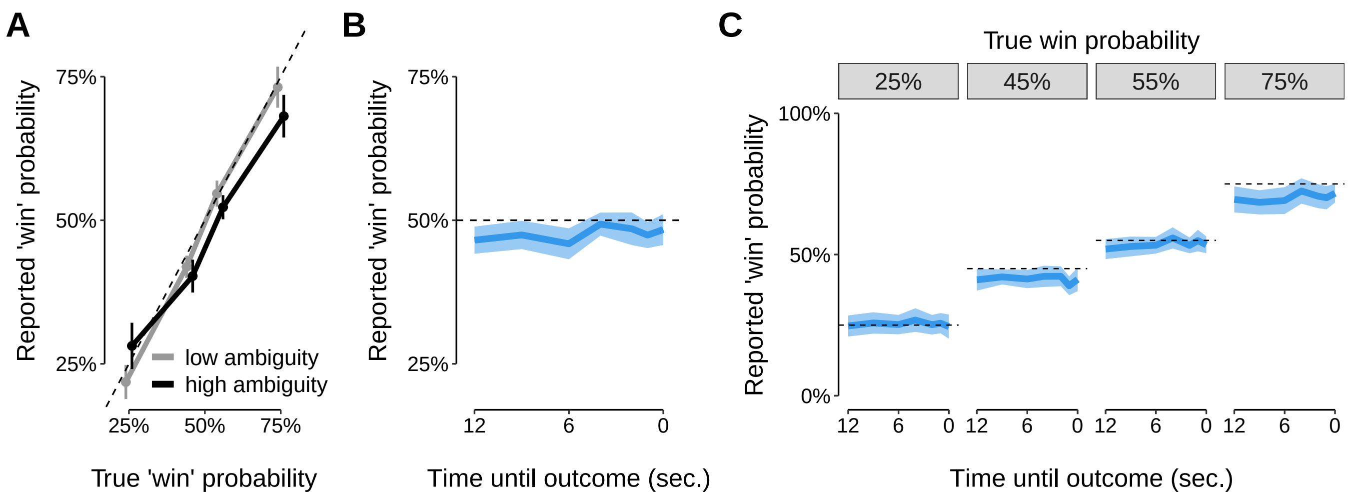

Figure 2: Behavioral results for Experiment 1. **A**: Mean reported win probability as a function of true win probability and ambiguity level (gray: low ambiguity; black: high ambiguity), marginalizing across different prompt times. Reported win probabilities were modulated less strongly by the true win probability in the high-ambiguity condition than in the low-ambiguity condition. The diagonal dashed line represents the line of equality. Points are horizontally jittered to avoid overplotting. **B**: Mean reported win probability as a function of time remaining until outcome reveal, marginalizing across different true win probabilities and ambiguity levels. There was no evidence that reported win probability was modulated by time until outcome. **C**: Mean reported win probability as a function of time remaining until outcome reveal (horizontal axis) and true win probability (plot facets), marginalizing across different ambiguity levels. Participants' reported win probability increased in line with changes in the true win probability, but there was no evidence that reported win probability varied according to the interaction of true win probability and time until outcome. Error bars/ribbons represent the 95% confidence interval of the mean. In panels B and C, the horizontal dashed lines represent the true win probability in each case.

related to participants' bonus payments, the belief elicitation process itself was not incentive-compatible; that is, there was no financial gain to be derived for participants from reporting their actual subjective beliefs about the likelihood of winning. Although non-incentive-compatible subjective probability reports such as these are routinely collected in cognitive science (e.g., Boddez et al., 2013), this differs from standard practice in behavioral economics, where incentive-compatibility is considered vital to ensuring the interpretability of subjective probability reports (e.g., Schlag, Tremewan, & Van der Weele, 2015).

Second, in our task there was a calculable 'correct' answer for the win probability of each gamble (i.e., an answer that was Bayes-optimal given the information provided). Given the close average correspondence between participants' reported beliefs and this 'correct' probability, we cannot rule out a form of socially desirable responding whereby participants reported estimates of the correct probability rather than their actual subjective beliefs. Notably, this issue would be expected to persist even with an incentive-compatible direct belief elicitation method as long as participants held the belief that they could maximize winnings by responding 'correctly'. Given these potential confounds, we next conducted a second experiment using the same basic waiting paradigm, but in which participants' subjective beliefs were elicited using an incentive-compatible method based on choice behavior.

Experiment 2

Method

Participants 60 new participants (37 female, 23 male) were recruited via the website Prolific to complete an online cognitive task. Participants were aged between 18 and 57 years (mean age 30.78, SD = 10.71). Participants were paid \$4 for participation, plus a bonus up to \$2 depending on task outcomes (mean bonus = \$1.17, SD = 0.12). Details of inclusion criteria and consent were otherwise as per Experiment 1.

Cognitive task The task in Experiment 2 was very similar to the task in Experiment 1, with one key change: rather than reporting beliefs via a probability slider, Experiment 2 employed choice-based incentive-compatible belief elicitation. Once per waiting period on each trial, participants were offered the choice either to continue waiting and accept the resulting outcome, or to 'cash out' of the gamble in exchange for an immediate payout of a reduced number of points (see Figure 1C). We reasoned that cash-out behavior would provide an incentive-compatible indication of participants' subjective beliefs, since higher expectations of a win should be accompanied by lower willingness to accept a cash-out offer.

To increase the precision of measurement in each cell of our design, we offered a smaller range of prior win probabilities in Experiment 2 (35%, 55%, or 75%), and all trials were presented with the same ambiguity level (3 of 10 cards face-down). Cash-out offers were calibrated relative to the expected value (EV) of each gamble: participants could be offered a cash-out amount of either 2.5, 1.5, or 0.5 points less than the true expected value of the gamble (e.g., for a win probability of 75% [EV = 7.5 points], cash-out offers could be either 5, 6, or 7 points). As in Experiment 1, we measured cash-out behavior at a number of distinct points during the waiting period (12, 10, 8, 6, 4, 2, or 0 seconds prior to reveal). Participants completed a total of 63 trials (3 win probabilitiies $\times$ 3 cash-out offer amounts $\times$ 7 offer times). All other details of the task implementation were as in Experiment 1.

Data exclusions To identify inattentive participants, five additional attention-check trials were randomly interspersed throughout the task. In these trials, there was an objectively correct choice for the cash-out decision (e.g., cash-out offer of 2 points when win probability was 100%). 8 participants (13.3% of sample) responded incorrectly to one or more attention check, and were excluded from all further analysis. As in Experiment 1, we also excluded trials in which participants clicked away from the browser window during the waiting period (202 trials excluded, 5.7% of total).

Data analysis Data were analyzed using a Bayesian mixed-effects logistic regression analysis as implemented in the `brms` package for R. Cash-out offer amount was coded relative to the Bayesian expected value of each gamble (i.e., EV minus 2.5, 1.5, or 0.5 points). All predictors were then grand-mean-centered prior to analysis. Analysis parameters were otherwise as specified in Experiment 1.

Results

Manipulation check As a manipulation check, we first examined the overall proportion of trials in which participants accepted a cash-out offer. On average, participants accepted the cash-out offer on 33.7% of trials (SD = 47.3). The probability of accepting a cash-out offer was modulated substantially by the value of that offer (mean proportion of cash-out choices for offers 2.5 points less than the gamble EV: 16.4%; for offers of EV minus 1.5 points: 29.1%; for offers of EV minus 0.5 points: 54.3%). Moreover, despite substantial heterogeneity in cash-out preferences, no participants displayed either floor or ceiling effects (cash-out probability range across participants: 1.6% to 85.7%). Taken together, these results give us confidence both that participants understood the task and that the range of cash-out offer values was reasonably calibrated for assessing their subjective beliefs.

Regression analysis Results of a Bayesian mixed-effects logistic regression analysis indicated that the probability of accepting a cash-out offer did not change as a function of the time remaining until the outcome ($\beta = 0.001$, 95% HDI $[-0.03, 0.03]$; Figure 3A). This flat temporal profile of choice behavior was invariant across different levels of gamble win probability ($\beta = 0.001$, 95% HDI $[-0.001, 0.002]$; Figure 3B) and different cash-out offer amounts ($\beta = -0.01$, 95% HDI $[-0.04, 0.03]$; Figure 3C). There was also no evidence for a three-way interaction ($\beta = -0.0002$, 95% HDI $[-0.002, 0.002]$).

Separately, and consistent with the descriptive statistics reported above, the regression analysis revealed that participants were more likely to accept a cash-out offer as the amount offered increased ($\beta = 1.41$, 95% HDI $[1.15, 1.68]$). We also found that participants were less likely to accept a cash-out offer as the underlying win probability of the gamble increased ($\beta = -0.02$, 95% HDI $[-0.04, -0.003]$).

Quantifying support for a null model As in Experiment 1, we next conducted an auxiliary analysis to directly quantify the support for the null hypothesis (i.e., that no aspect of participants' cash-out behavior changed as a function of time until outcome reveal). Once again, we used Bayesian Model Averaging to estimate the relative support for a full mixed-effects logistic regression model that included main effects and interactions of time until outcome, relative to a reduced model in which these effects and interactions were not included. As in Experiment 1, the results of this analysis indicated that the posterior probability of the null model was far higher than that of the full model including effects of time until outcome (estimated posterior probability of 0.99 for the null model, versus 0.01 for the full model).

General Discussion

Previous studies have shown that expectations regarding the outcome of a future event tend to decline over time as the event approaches (Gilovich, Kerr, & Medvec, 1993; Shepperd et al., 1996; Sweeny & Krizan, 2013). In the present study, we investigated whether this pattern of temporal declines in expectations could also be elicited within a controlled cognitive task involving a short wait period and low-stakes monetary gambles. Taken together, our results showed little evidence for temporal declines in expectations in this task: both participants' self-reported beliefs regarding gamble outcomes (Experiment 1) and their willingness to 'cash out' of gambles (Experiment 2) were constant across the delay prior to the outcome reveal. Comparison of competing regression models indicated that data statistically supported the null hypothesis, rather than being a product of insufficient statistical power.

Our results should not be interpreted as undermining the status of temporal declines in expectations as a psychological phenomenon. This effect has been demonstrated repeatedly in a number of real-world and laboratory settings (Sweeny & Krizan, 2013), and the cognitive task that we developed here is different in several important respects from those contexts. As such, our study does not constitute a direct (or even conceptual) replication attempt for the phenomenon as a whole. Instead, our results can be thought of as helping to specify the boundary conditions under which temporal declines in expectations occur. Viewed in this light, our findings demonstrate that temporal declines in expectations are not an invariant property of human expectations during a waiting period *in general*, but are rather a context-dependent phenomenon.

A natural follow-up question is: what features of a waiting

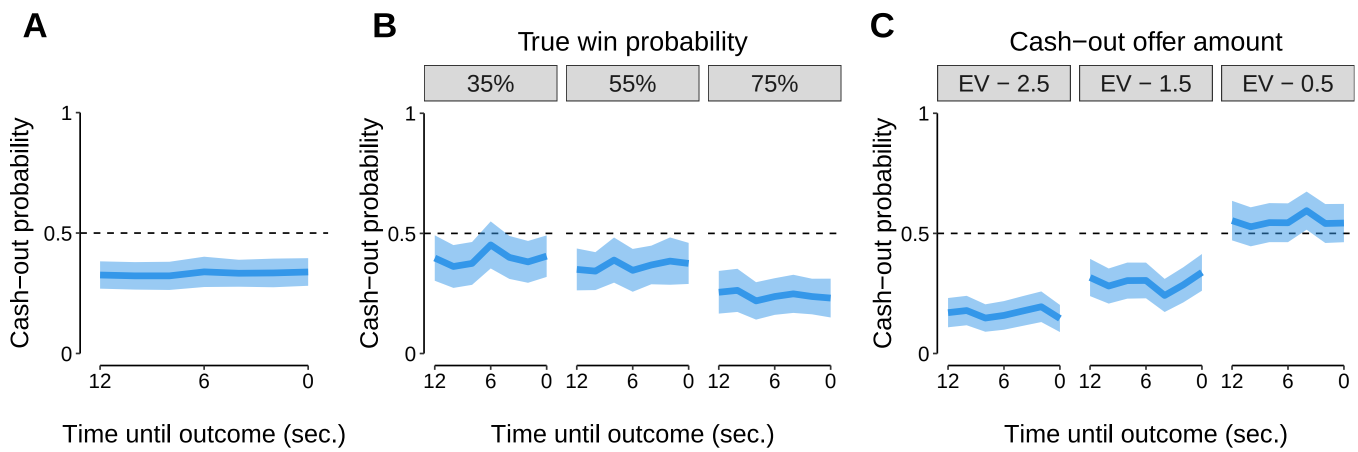

Figure 3: Behavioral results for Experiment 2. **A**: Mean probability of accepting the 'cash-out' offer as a function of time remaining until outcome reveal (in seconds), marginalizing across different underlying true win probabilities and offer amounts. There was no evidence that participants' cash-out probability differed as a function of time until outcome. **B**: Mean cash-out probability as a function of time remaining (horizontal axis) and true win probability (plot facets), marginalizing across offer amounts. Participants were less likely to cash out as the true win probability increased, but there was no evidence for an interaction between true win probability and time until outcome. **C**: Mean cash-out probability as a function of time remaining (horizontal axis) and cash-out offer amount (plot facets), marginalizing across true win probability. Cash-out offer amounts are relative to the expected value (EV) of each gamble. Participants were more likely to cash out as the value of the cash-out offer increased, but there was no evidence that cash-out probability varied as a function of the interaction between cash-out offer amount and time until outcome. Error ribbons represent the 95% confidence interval of the mean. Horizontal dashed lines indicate the indifference point between cashing out and waiting.

situation produce temporal declines in expectations? In situations where temporal declines in expectations are observed, such as in students awaiting a grade or patients awaiting a medical test result, the waiting period is typically prolonged (on the order of multiple days or weeks), and the outcome stakes are relatively high. In our task, by context, the waiting period was short (12 seconds) and the outcome stakes were low. At a first pass, therefore, one might speculate that both factors contributed to participants' stable expectations in the present study. However, the literature includes conflicting findings regarding the importance of high-stakes outcomes: although greater declines in expectations have been reported for high-stakes outcomes in some instances (e.g., K. M. Taylor & Shepperd, 1998), overall a meta-analysis found that temporal declines in expectations were more pronounced for low-stakes outcomes than for high-stakes outcomes (Sweeny & Krizan, 2013).

This suggests that the null results of the present study might be primarily attributable to the short waiting period employed in our task. If so, then we would predict that temporal declines in expectations should emerge at longer waiting periods even with the low-stakes gambles employed in our task. The shortest duration over which temporal declines in expectations have been observed is 20 minutes (Terry & Shepperd, 2004); an important topic for future research is, therefore, at what duration expectation declines begin to emerge.

An alternative possibility is that the nature of the information that is presented after the delay might be important in driving temporal declines in expectations. Many of the settings in which temporal declines in expectations have been elicited involve subjective reviews of one's own performance or expectations regarding the self. In the present study, although payoffs were personally relevant in the sense of affecting participants' winnings, they may have been perceived as less personally relevant than outcomes in previous studies of temporal declines in expectations. Future research should therefore also examine whether declining expectations are specific to the evaluation of one's prior actions over time (rather than probabilities of external events).

More broadly, further research is required to determine the cognitive determinants of temporal declines in expectations. One influential theory is that temporal declines in expectations stem from individuals' attempts at affect management (Shepperd & McNulty, 2002; Sweeny & Shepperd, 2010). Under this hypothesis, declining expectations stem from efforts to balance the psychological rewards of optimism against the anticipated psychological shock of future disappointment. A promising avenue for future cognitive theories of expectation declines might therefore be to extend affect-management theories using recent computational models that more precisely specify the cognitive appraisal processes underlying shifts in affect (Rutledge, Skandali, Dayan, & Dolan, 2014; Eldar, Rutledge, Dolan, & Niv, 2016; Bennett, Davidson, & Niv, 2021).

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