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The Causes and Consequences of Drifting Expectations

William J. Villano[1], Noah I. Kraus[1], T. Rick Reneau[2], Brittany A. Jaso[3], A. Ross Otto[4], and Aaron S. Heller[1]
[1]Department of Psychology, University of Miami; [2]Department of Psychiatry, Washington University in St. Louis; [3]Reliant Medical Group, OptumCare, Worcester, MA; and [4]Department of Psychology, McGill University

Abstract
Awaiting news of uncertain outcomes is distressing because the news might be disappointing. To prevent such disappointments, people often "brace for the worst," pessimistically lowering expectations before news arrives to decrease the possibility of surprising disappointment (a negative *prediction error*, or PE). Computational decision-making research commonly assumes that expectations do not drift within trials, yet it is unclear whether expectations pessimistically drift in real-world, high-stakes settings, what factors influence expectation drift, and whether it effectively buffers emotional responses to goal-relevant outcomes. Moreover, individuals learn from PEs to accurately anticipate future outcomes, but it is unknown whether expectation drift also impedes PE-based learning. In a sample of students awaiting exam grades ($N = 625$), we found that expectations often drift and tend to drift pessimistically. We demonstrate that bracing is preferentially modulated by uncertainty; it transiently buffers the initial emotional impact of negative PEs but impairs PE-based learning, counterintuitively sustaining uncertainty into the future.

Keywords
expectation, expectation drift, bracing, emotion, learning, prediction error, naturalistic methods, ecological momentary assessment

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In daily life, people frequently await important academic, health, and professional news. Yet regardless of whether the news is good or bad, waiting for the outcome is often distressing because the outcome may be disappointing (Sweeny, 2018; Sweeny & Cavanaugh, 2012). Evidence suggests that individuals adopt pessimistic expectations before outcomes are revealed to preempt disappointment (Shepperd et al., 2000; Sweeny & Krizan, 2013; Taylor & Shepperd, 1998). This preemptive response to an uncertain, potentially disappointing outcome is often termed *bracing* ("bracing for the worst"; Taylor & Shepperd, 1998). These pessimistic drifts in expectation have been considered adaptive (Sweeny & Dooley, 2017; Sweeny & Howell, 2017; Sweeny & Shepperd, 2010) because when people lower their expectations, the outcome is less likely to be worse than their new expectations (Shepperd et al., 2000).

Evaluating how often and in which direction expectations drift is critical for at least three reasons. First, computational-learning and decision-making research typically treat expectations as fixed during the time between decisions and outcomes (e.g., Gold et al., 2012; Rutledge et al., 2014) and compute prediction errors on the basis of inferred outcome probabilities from computational models (Daw, 2011). Yet, if in everyday life expectations do drift as outcomes near, experimental decision-making research should account for such phenomena. Second, because expectations dictate our emotional reactions when we receive an outcome (Shepperd & McNulty, 2002; Sweeny & Shepperd, 2010), understanding whether and how expectations drift is necessary to accurately model emotion. Because prior work has found that prediction errors drive emotional responses (Rutledge et al., 2014; Villano et al., 2020),

Corresponding Author:
Aaron S. Heller, University of Miami, Department of Psychology
Email: aheller@miami.edu

pessimistic shifts in expectation alter the set point for prediction errors, reducing the possibility of disappointment (a negative prediction error; Sweeny & Krizan, 2013). A prevailing hypothesis is that bracing reduces the initial shock of disappointment (Shepperd et al., 2005; Sweeny & Howell, 2017; Sweeny & Shepperd, 2010), but capturing such an effect requires repeated measures of emotion that are precisely time-locked to the moment when news is revealed. Currently, evidence of bracing's emotional benefits rests largely on work demonstrating that pessimism—having a lower expectation than one's peers—increases one's chances of pleasant surprises (Sweeny & Shepperd, 2010; but see Krizan & Sweeny, 2013). However, previous studies have not combined repeated assessments of expectations with repeated measures of emotion after the outcome has been revealed (i.e., to determine whether expectations shifted). And third, in addition to driving emotion, prediction errors are learning signals indicating how our expectations are inaccurate and how our expectations should be updated to better align with reality (Pavlov, 1928; Rescorla & Wagner, 1972). As a result, prediction-error-driven learning facilitates accurate expectations in the face of uncertainty, minimizing the likelihood of future surprises (Sutton & Barto, 1998). Yet we do not know whether expectation drift affects prediction error–based learning (in addition to buffering emotion). Thus, it is unclear whether the putative emotional benefits of becoming pessimistic have any long-term impact on learning.

Prior work has suggested that expectations may drift for several reasons. First, one theory suggests that people lower their expectations to avoid disappointment, bracing themselves for a negative outcome (Shepperd et al., 2000; Sweeny et al., 2006; Taylor & Shepperd, 1998). In these cases, pessimistically drifting expectations are thought to represent efforts to manage future emotions (e.g., disappointment, grief), or to preemptively mobilize resources to deal with a negative outcome. They could also represent magical thinking—for instance, beliefs that expectations may influence actual outcomes (Carroll et al., 2006). However, expectations may drift downward for other reasons. Indeed, acquiring new information about likely outcomes during a waiting period can drive expectations to change upward or downward (Sweeny et al., 2006). Thus, although bracing for disappointment strictly manifests in pessimistic drift, new information can shift expectations optimistically or pessimistically. Because of the lack of real-world, prospective empirical research, however, we have a limited understanding of whether pessimistic or optimistic shifts predominate in real-world waiting periods and what factors influence a drift in expectations as outcomes approach.

Statement of Relevance

People often lower their expectations before uncertain news is revealed, bracing themselves for the worst. In theory, this could adaptively manage distress in uncertain contexts: Lowering one's expectations reduces the chance of an unexpected disappointment. However, surprising outcomes drive emotions and drive learning. Thus, changing our expectations to forestall emotional upsets may hinder our ability to learn what is likely to occur in the future. Using mobile-phone surveys to track college students' expected exam grades, we demonstrate that people's expectations often shift pessimistically, and they do so after unexpected upsets. Moreover, despite lessening the short-term emotional impact of upsetting news, we find that pessimistic expectation shifts impede long-term learning, increasing the chances of surprising outcomes in the future. Rather than assume our expectations are static, future research should account for the existence of shifting expectations and its consequences for emotion and learning.

Second, other work suggests that increased negative affect may be a cause of pessimistic expectation shifts. Because anticipating consequential, personally important outcomes (such as awaiting one's results on an important exam; Carroll et al., 2006; Krizan & Sweeny, 2013; Sweeny et al., 2006) often provokes negative affect, it is not surprising that prior work finds that people lower their expectations to manage rising anxiety during waiting periods (Sanna, 1999; Sanna et al., 1999; Shepperd et al., 1996, 2005; Taylor & Shepperd, 1998; Wilson & Sweeny, 2023). Consistent with this idea, pessimistic drift is typically observed in close proximity to the "moment of truth" (i.e., when an outcome is revealed; Sweeny et al., 2006).

Third, and last, some work suggests that people are more likely to lower their expectations when they are less familiar with the outcome (Sweeny & Krizan, 2013)—perhaps because they are less certain of the accuracy of their expectations. However, no studies have evaluated whether uncertain expectations are more likely to drift. Moreover, because there are multiple forms of uncertainty, it is important to understand what type of uncertainty may moderate expectation shifts. Forms include expected uncertainty (which occurs in the context of completely unfamiliar events; Berlyne, 1970), unexpected uncertainty (which occurs in the context of familiar events, if recent outcomes of those events were unexpected; Dayan & Yu, 2002;

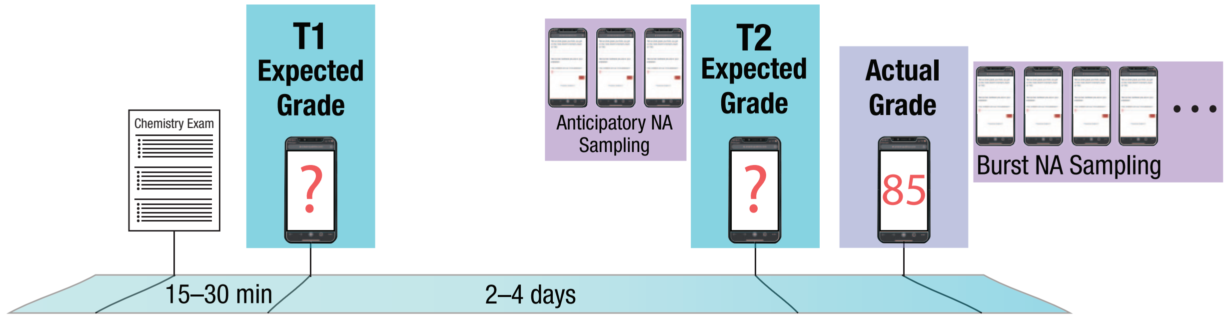

Fig. 1. Ecological momentary assessment study design. For each exam, expectations were sampled via cell-phone surveys at two time points, immediately after each exam was completed (T1) and immediately before participants received their grades (T2; between 2–4 days later). NA = negative affect.

Soltani & Izquierdo, 2019), and subjective uncertainty (which manifests in a lack of confidence in one's expectations; Dequech, 1999).

The present study advances this area of research by investigating the instability of 625 university students' expectations while they awaited a goal-relevant, high-stakes outcome. Across four to five exams, we used cellphone-based ecological momentary assessment (EMA) to sample students' expected grades on midterm exams but did so twice per exam—immediately after students completed exams, and again immediately before they received their grades. This enabled us to determine whether and how expectations drifted as the outcome neared, as well as the causes and consequences of such expectation drift. In line with our previous work (Villano et al., 2020, 2023), course professors provided us with actual exam grades, which allowed us to control the release of those grades to students and compute exam grade prediction errors. We then used event-locked EMA to measure the time courses of participants' emotions, both before seeing their grades (anticipation) and for the ensuing 12 hrs after seeing grades. Our central aims were to determine (a) whether expectations drift in this naturalistic, high-stakes context, (b) if expectations do drift, whether they preferentially drift pessimistically, (c) which factors predict an increase in expectation drift (including negative emotion and uncertainty), (d) whether pessimistic expectation drift moderates the emotional impact of exam grade prediction errors, and, last, (e) whether pessimistic expectation drift impacts PE-based learning.

Open Practices Statement

All data needed to evaluate the conclusions in the article are present in the article or in the Supplemental Material available online. Data and analysis code are available upon reasonable request to the authors. The present study was not preregistered.

Method

Participants

Participants were 740 undergraduate students recruited from university chemistry classes between August 2019 and December 2020. Over three semesters (Fall 2019, $n = 187$; Spring 2020, $n = 315$; Fall 2020, $n = 436$, with 198 students enrolled in more than one semester), students in three different chemistry courses (General Chemistry, Organic Chemistry 1, Organic Chemistry 2) participated in a semester-long *ecological momentary assessment* (EMA) study that assessed exam-grade expectations for the four to five midterm exams in each class (Fig. 1). Study enrollment was time limited and ended prior to the first exam in each chemistry class.

Participants who did not participate sufficiently in EMA sampling (i.e., provide grade predictions for at least two consecutive exams) were excluded from the final analysis sample (115 participants were excluded). This yielded a final analysis sample of 625 participants.

Procedure

Initial laboratory sessions. At the start of academic semesters, students who were interested in the study participated in an initial laboratory session during which they provided informed consent per study protocol (the study was approved by the university's Institutional Review Board, IRB No. 20180529). Following the onset of the COVID-19 pandemic in Spring 2020, initial laboratory sessions were conducted remotely via video teleconferencing. Participants authorized the study team to access their exam grades from course professors: Before exam grades were posted for students to view, chemistry professors provided the study team with the exam grades of study participants. Participants provided contact information for distribution of EMA surveys and were informed that surveys would be distributed via text messages (SMS) as a URL link to their mobile phones using the Qualtrics online survey platform (Qualtrics, 2020). Thus, all participants were required to have a cell phone capable of internet access and able to receive text messages. To incentivize completion of EMA surveys, we compensated participants with course extra credit proportional to their EMA completion rates.

Measurement of daily positive and negative affect. Every other day throughout the academic semester (baseline sampling), and more frequently both before (anticipatory sampling) and after viewing exam grades ("burst" sampling), participants were prompted via text message to complete brief EMA self-report surveys of momentary positive and negative affect. Self-reported positive and negative affect comprised a subset of items derived from the Positive Affect/Negative Affect Schedule (PANAS; Watson et al., 1988). These items, which assessed participants' current feeling of a range of emotions, were selected to sample across dimensions of affective valence and arousal (Russell, 1980). For each emotion item, participants rated the current intensity of that emotion on a visual analog scale (i.e., slider bar) that ranged from 0 (e.g., *not at all happy*) to 100 (e.g., *very happy*).

For each survey response, momentary positive-affect and negative-affect composite scores were derived from participants' responses to emotion items. Momentary positive affect was computed as the mean score for survey items that assessed the emotions "happy," "excited," "attentive," and "relaxed." Momentary negative affect was computed as the mean score for survey items that assessed the emotions "upset," "irritable," and "anxious."

Measurement of exam-grade expectations and contextual variables. After completing each midterm exam but before receiving their grades, participants reported the exam grade they expected to receive. Participants reported their expected grades at two separate time points: immediately after completing each exam (T1) and immediately before receiving their grades (T2). Participants' expectations were free to drift between T1 and T2 surveys. Although exams were administered online during the Spring 2020 semester (because of the effects of the COVID-19 pandemic on in-person learning), the relative timing of EMA surveys did not change.

Initial expectations (T1). Within 30 min of the conclusion of each midterm exam, participants were prompted via text message to report the grade they expected to receive on that exam. Exam-grade expectations were entered into a survey text box. Only numeric responses between 0 and 100 were accepted, and participants were prompted to reenter their expected grade if their response was not within this range. Participants were also prompted to report their subjective confidence in their expectation on a visual analog scale that ranged from 0 (*not at all confident*) to 100 (*very confident*) in increments of 1 point.

Anticipatory expectations and affective sampling (T2). Within 2 to 4 days of taking the exam and providing the initial (T1) grade expectation, participants were notified that their grades would be released in "two hours and fifteen minutes." Upon receiving this notification, and at 45-min intervals for the remaining 2 hrs and 15 min (the anticipation period), participants were prompted to complete EMA surveys measuring current positive affect and negative affect (termed *anticipatory positive affect* and *anticipatory negative affect*). Participants received up to three anticipatory affective surveys during this anticipation period. At the end of the anticipation period, participants were notified that grades were ready to be viewed through our online interface. Before they could view their grades, participants reported for a second time (T2) their expected exam grade and their confidence in their expectation.

Measurement of affective reactivity to exam grades. Subsequent EMA self-report surveys of momentary affect were yoked to the moment participants viewed their exam grades (as described in Villano et al., 2020). Positive affect and negative affect were sampled every 45 min for the remainder of the day (until 12:30 a.m. ET). For the purposes of this study, positive affect was disregarded and only negative affect was used in analyses.

Preprocessing and calculation of study variables

Exam-grade prediction errors. Exam-grade prediction errors (PEs) were computed as the difference between participants' actual grades on an exam and the grades they expected to receive on that exam:

$$PE_{ij} = O_{ij} - E(\mathrm{T1})_{ij}, \tag{1}$$

where i denotes observations for a given participant, j denotes observations for one of the exams, PE represents prediction error, E represents an exam-grade expectation recorded at T1 (immediately after taking an exam), and O represents the exam-grade outcome received. We chose the initial expectation to compute prediction errors to align with our previous work (Villano et al., 2023) and to ensure that the magnitude of prediction errors could not be influenced by expectation drift (which could occur if we used the T2 expectation in computing prediction errors).

Exam-grade prediction accuracy. In theory, pessimistic expectation drift alters downstream emotion by shifting prediction errors to be more positive (Taylor & Shepperd, 1998). Beyond the hypothesized short-term emotional benefit, we tested whether expectation drift may also alter prediction errors such that prediction-error-driven learning is affected. Thus, we tested whether drift resulted in less accurate expectations on future exams. To test whether expectation drift impacted prediction-error-driven learning, we first computed the accuracy of participants' T1 exam-grade expectations, which was based on the size of their T1 prediction errors:

$$Accuracy_{ij} = 100 - |\, PE_{ij} \,|. \quad (2)$$

Here, larger prediction errors, regardless of valence, indicate poorer accuracy. To compute an intuitive metric representing expectation accuracy, we subtracted prediction-error magnitude (i.e., absolute value of prediction error) for each exam from 100, so higher accuracy values were associated with smaller prediction errors. Importantly, accuracy was derived from T1 expectations and was thus not influenced by expectation drift (i.e., the change between T1 and T2 expectations).

Expectation drift. To determine whether participants' expectations drifted before viewing their grades, we computed a continuous measure of expectation drift as the difference between participants' T2 and T1 expectations for each exam:

$$Expectation\ Drift_{ij} = E(\mathrm{T2})_{ij} - E(\mathrm{T1})_{ij}, \quad (3)$$

where i denotes observations for a given participant, and j denotes exam. Positive values represent optimistic drift, or increases in expectations, whereas negative values represent pessimistic drift, potentially capturing bracing behavior.

Baseline negative affect. For each participant, we computed a baseline affect score as a participant's mean negative affect throughout the baseline-sampling period (not including negative affect measured in the aftermath of receiving exam grades).

Anticipatory negative affect. Anticipatory negative affect was computed as a participant's average momentary negative affect recorded during the 2-hr-and-15-min anticipation period that preceded the release of exam grades.

Average negative affect responses to exam grades. We used the frequently sampled negative emotions occurring during the burst-sampling periods (triggered after students saw their grades) to test the impact of pessimistic expectation drift on emotional responses. To generate measures that represented emotional responses to exam grades as displacement from an individual's affective baseline, we centered these momentary measures of emotion to each participant's baseline negative affect score (baseline-corrected NA = momentary NA - baseline NA). We then computed average negative-affect scores within three time windows to test whether (a) pessimistic drift impacted overall emotional responses across a 12-hr window, (b) whether pessimistic drift impacted initial emotional reactivity to exam grades, and (c) whether pessimistic drift impacted longer-term emotional responses. To do this, we truncated negative-affect time courses to a maximum length of 12 hrs, and they were averaged within the entire 12-hr period, within the first hour of sampling only, and within the final 4 hrs of the burst-sampling period (hours 8–12).

Statistical modeling

Statistical analyses were conducted using R (R Core Team, 2017). Distributions of variables were assessed for normality, and descriptive statistics for each variable were extracted prior to statistical modeling. Given the hierarchical structure of the data set (i.e., multiple exams within participant, and multiple participants within cohorts), we used multilevel regression models to account for participant-specific and cohort-specific effects. Linear mixed-effects models were constructed and evaluated using the *lme4* package in R (Bates et al., 2018).

To ensure accurate parameter estimation in statistical models, we censored outlying data prior to analysis. In line with our prior work (Villano et al., 2023), outlying prediction errors that were greater than 50 or less than −50 and expectation updates (between exams) greater than 50 or less than −50 were censored. Additionally, exams for which participants reported expectation drift greater than 50 or less than −50 were censored prior to analyses (0.11% of trials).

Do expectations drift?

To test whether participants' expectations drifted while they waited to see their exam grades, we specified a linear mixed-effects model in which the intercept represented the mean expectation drift while accounting for within-participant dependencies (i.e., repeated exams within participants):

$$Expectation\ Drift_{ij} \sim 1 + (1|cohort\,/\,i), \quad (4)$$

where i defines individual participants as random-effects levels, and the term *cohort* accounts for the dependencies within the same semester (i.e., cohort). We hypothesized that on average, expectation drift would be negative (i.e., pessimistic) and consistent with bracing behavior (Sweeny, 2018; Sweeny & Krizan, 2013).

What factors influence expectation drift?

Prior work has suggested—but has not empirically tested—that expectation drift is influenced by factors such as the current degree of uncertainty (Sweeny et al., 2016), and one's affective state during a waiting period (Sweeny & Shepperd, 2007). Thus, we performed an analysis to evaluate whether expectation drift was influenced by (a) uncertainty due to a lack of experience or familiarity, (b) subjective expectation confidence indicating a lack of certainty in expectations, (c) uncertainty because of prior prediction errors, and (d) anticipatory negative affect. We first tested whether each predictor (operationalized in detail below) independently drove pessimistic expectation drift. We then tested predictors jointly in competing models to determine the combination of variables that best predicted expectation drift. Last, to identify the unique effects of each predictor and determine the most robust causes of expectation drift, we jointly evaluated the proposed set of predictors in a single, maximally specified model, and removed less-impactful predictors via backward elimination.

Uncertainty due to a lack of familiarity. As participants gained familiarity by taking more exams, we reasoned that uncertainty surrounding exam grades would decrease. Assuming that uncertainty in grade expectations decreased with each additional exam, we hypothesized—as prior researchers have proposed (Sweeny & Krizan, 2013)—that participants' expectations would become more stable (i.e., drift less) as the semester elapsed. To test this, we formulated a variant of the model presented in Equation 4 with time (i.e., exam number) specified as a predictor:

$$Expectation\ Drift_{ij} \sim j + (1|cohort/i), \qquad (5)$$

where j represents the exam. We predicted that participants would reduce their expectations the most at the first exam of the semester, when unfamiliarity with exams and uncertainty surrounding grades were maximal.

Uncertainty due to lack of subjective confidence in expectation. Although participants did not report directly on the degree of uncertainty surrounding exam grades, we operationalized participants' self-reported confidence in grade expectations as an indicator of subjective uncertainty. We hypothesized that participants who reported less confidence in their expectations were less certain about their exam grades and thus may be more likely to reduce their expectations to avoid potential disappointment. To test whether this was the case, we specified a linear mixed-effects model in which expectation drift was regressed onto participants' self-reported confidence in their T1 expectations:

$$Expectation\ Drift_{ij} \sim Confidence(\mathrm{T1})_{ij} + (1|cohort/i). \qquad (6)$$

We hypothesized that lower confidence would predict more pessimistic expectation drift—potentially indicating a greater propensity to brace for disappointment.

Uncertainty due to prior surprise. In addition to a lack of familiarity with exams, highly surprising outcomes on the preceding exam (a large prediction error) may also constitute a form of uncertainty that is not attenuated by experience, but rather reinforced by it (so-called *unexpected uncertainty*). To evaluate whether this form of experience-driven uncertainty led to greater expectation drift, we constructed a linear mixed-effects model in which expectation drift was regressed onto participants' prediction errors on the preceding exam:

$$Expectation\ Drift_{ij} \sim PE_{i\,j-1} + (1|cohort/i). \qquad (7)$$

We hypothesized that increasingly negative prediction errors on the preceding exam would predict more pessimistic drift regarding the current exam, which might suggest that participants lower their expectations when prior instances of a waiting period manifested in surprise or disappointment.

Anticipatory negative affect. Last, in line with an existing theory (Shepperd et al., 1996; Sweeny & Howell, 2017; Sweeny & Shepperd, 2007), we hypothesized that participants who experienced elevated anticipatory negative affect would exhibit more pronounced downward adjustments to their expectations. Using a linear mixed-effects model, we tested whether expectation drift varied as a function of people's anticipatory negative affect prior to receiving their grade, and included participants' baseline NA scores as a covariate:

$$Expectation\ Drift_{ij} \sim Anticipatory\ NA_{ij} + Baseline\ NA_i + (1|cohort/i). \qquad (8)$$

Identifying the best-fitting model predicting expectation drift

To determine which combination of variables best predicted expectation drift, we conducted a model comparison analysis over mixed-effects models containing each possible permutation of expectation-drift predictors. A Bayesian information criterion (BIC) was computed for each model, and the model that yielded the lowest BIC was selected as the best-fitting model.

To determine which variables most strongly predicted expectation drift, we formulated a single mixed-effects model in which drift at the current exam was simultaneously regressed onto each of the aforementioned factors: prior prediction error, anticipatory negative affect, confidence in expectations, and exam number. Testing all predictors in a single, maximally specified model enabled us to determine the unique effects of each variable in predicting expectation drift:

$$\begin{aligned} &\mathit{Expectation\ Drift}_{ij} \sim PE_{ij-1} + \mathit{Anticipatory\ NA}_{ij} \\ &\quad + \mathit{Baseline\ NA}_i + \mathit{Confidence}(\mathrm{T1})_{ij} \\ &\quad + j + (1 \mid \mathit{cohort} / i). \end{aligned} \tag{9}$$

As in the model presented in Equation 8, baseline negative affect was included as a covariate to account for between-participant differences in average negative affect. To further elucidate the factors with the greatest influence on expectation drift, we then performed a backward elimination of predictors in the fully specified model in Equation 9 using partial *F* tests.

Does pessimistic expectation drift buffer negative-affective responses to exam-grade prediction errors?

It has been argued that one of the primary functions of bracing is to reduce the impact of negative prediction errors, which may buffer negative emotions following disappointing outcomes. Here, we tested whether pessimistic expectation drift indeed altered affective responses to exam grade prediction errors. First, to determine whether pessimistic expectation drift—relative to optimistic drift—moderated negative-affect responses to prediction errors over the entire 12-hr burst-sampling period, we fit a linear mixed-effects model in which the interaction between exam-grade prediction errors and a binary factor representing the direction of expectation drift (i.e., optimistic or pessimistic) predicted average negative affect over the full 12-hr burst-sampling period. Additionally, to determine whether drift in either direction altered both initial emotional reactivity as well as longer-term emotional responses, we fit the same model to average negative affect calculated over the first hour of burst sampling (i.e., initial emotional reactivity) and to average negative affect over the final 4 hr of the sampling period:

$$\begin{aligned} &NA_{ij} \sim PE_{ij} * \mathit{Expectation\ Drift\ Direction}_{ij} \\ &\quad + (1 \mid \mathit{cohort} / i), \end{aligned} \tag{10}$$

where NA was construed in three separate models as average negative affect computed (a) over the full burst-sampling period, (b) over the first hour of emotional reactivity, and (c) over the final 4 hrs of the sampling period (i.e., hours 8–12).

Does expectation drift impact prediction-error-driven learning?

Last, to evaluate the possibility that drifting expectations impact how one learns from subsequent prediction errors, we tested whether expectation drift at one exam is linked to differences in expectation accuracy at the following exam. To test this, we formulated a linear mixed-effects model in which expectation accuracy at the upcoming exam was predicted by expectation drift at the preceding exam:

$$\begin{aligned} &\mathit{Accuracy}_{ij+1} \sim \mathit{Expectation\ Drift}_{ij} + j \\ &\quad + \mathit{Accuracy}_{ij} + (1 \mid \mathit{cohort} / i). \end{aligned} \tag{11}$$

Because prediction-error-driven learning causes individuals' expectations to become more accurate as experience accrues, we included exam number (*j*) as a covariate in the model. Given that drifting expectations alter prediction errors, we hypothesized that expectation drift in any direction would imbue prediction-error learning signals with noise, leading to less effective prediction-error-driven learning and less accurate expectations at the next exam.

Results

When expectations drift, they do so pessimistically

First, we tested whether participants' expectations drifted while they anticipated their exam grades. Expectation drift, computed as the difference between participants' T2 and T1 expectations for each exam, had a frequency distribution with a mode of 0 (Fig. 2), which indicated that people's expectations most often did not drift during these waiting periods. However, there were also notable spikes in the frequency distribution at expectation-drift values of −10, −5, 5, and 10, indicating that when people's expectations did drift, they tended to drift in even increments of half-letter grades (i.e., 5 percentage points). Linear mixed-effects results, which accounted for within-participant variance in expectation drift, indicated that on average, participants reduced their expectations by −2.74 points ($SE = 0.16$, $p = .003$; see Table 1 for all linear mixed-effects regression statistics)—an effect that was small in magnitude but highly robust ($t = -17.21$). More specifically, of the 2,695 cases in which participants provided both T1 and

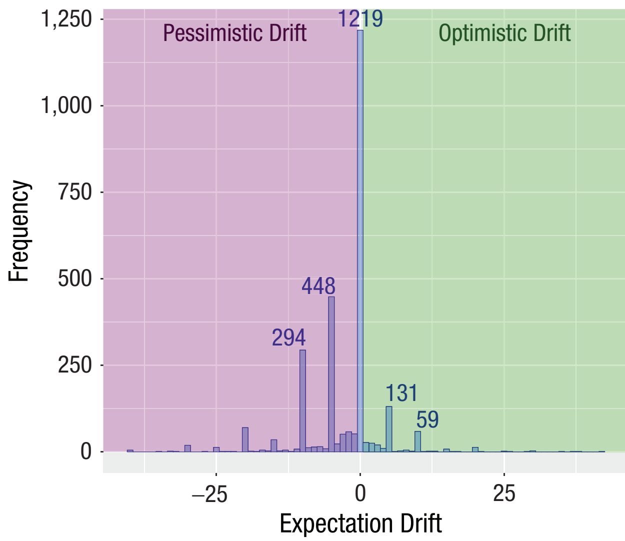

Fig. 2. Distribution of exam grade expectation drift. Participants reported their exam-grade expectations at two time points: immediately following each exam (T1) and prior to receiving their grade (T2). Pessimistic drift between T1 and T2 expectations indicates that people's expectations went down over time; this is represented on the left half of the distribution. Optimistic drift is represented on the right half. Expectation drift was primarily negative, suggesting that participants tended to lower their expectations between T1 and T2.

T2 expectations, a majority showed some drift (1,476 cases, or 54.77%). As noted above, however, the modal amount was no drift at all (1,219 cases; 45.23%). A similar proportion, 42.78% of cases (1,153 cases), showed pessimistic drift, and a relatively small proportion of cases (323 cases; 11.99%) showed optimistic drift. This finding aligns with prior accounts of bracing during uncertain waiting periods (Carroll et al., 2006; Shepperd et al., 1996, 2000; Sweeny et al., 2006), and replicates prior investigations of bracing while awaiting exam-grade results (Gilovich et al., 1993; Sanna, 1999; Shepperd et al., 1996, 2005).

Modeling expectation drift ordinally

Although the distribution of expectation drift was approximately normal, the aforementioned modes in the distribution at −10, −5, 0, 5, and 10 suggest that people's expectation drift may be best construed as an ordinal rather than a continuous variable. Thus, to account for the spikes in this distribution when predicting expectation drift as an outcome, we separately fit Bayesian regression models with cumulative links that treated expectation drift ordinally (i.e., with categories representing specific levels of expectation drift). Methods and results for these ordinal models, which replicate the models treating expectation drift as Gaussian, are reported in the Supplemental Material.

What causes expectations to drift?

With experience, people's expectations become more stable. We tested in several ways the hypothesis that pessimistic expectation drift is influenced by uncertainty. First, we tested whether expectation drift is predominantly pessimistic at the initial exam, but becomes less pessimistic with each additional exam. Indeed, this was the case, $b_{\text{exam}} = 0.26$ (0.11), $p = .02$ (see Fig. 3). People's expectations were less likely to drift downward as they gained familiarity with exams over the semester. This suggests that expectations drift more under some circumstances than others, and furthermore, that expectation drift is dynamic, changing as people gain familiarity with the event or context.

Pessimistic drift is linked to lower confidence in initial expectations. To further examine whether expectation drift was influenced by uncertainty, we tested whether drift was predicted by participants' self-reported confidence in their prediction of the grade they would receive. We assumed this measure of confidence to be a proximal indicator of subjective uncertainty surrounding exam-grade outcomes. Results revealed an association between self-reported confidence in exam-grade expectations and expectation drift, $b_{\text{confidence}} = 0.02$ (0.01), $p = .01$: Participants who reported lower confidence in their expectation for a given exam reduced their expectations more before receiving their grades on that exam.

Expectation drift is linked to prior surprise (prediction errors). Although uncertainty may emerge from a lack of prior experience, uncertainty can also emerge when prior experiences have been unpredictable. For instance, unexpected uncertainty (Dayan & Yu, 2002; Soltani & Izquierdo, 2019) suggests that, despite having experience in an environment, one's model of that environment can still be inaccurate and require updating. Indeed, some qualitative work suggests that this form of experience-driven uncertainty may drive expectations to drift pessimistically (Ockhuijsen et al., 2013). Thus, we tested whether expectation drift was linked to previous exam grade prediction errors, which index both the extent to which and manner in which one's grade on the preceding exam was unexpected (by prediction-error magnitude and sign—i.e., positive or negative—respectively). In line with our hypothesis, people who experienced negative prediction errors on the preceding exam were more likely to display pessimistic expectation drift for the current exam, $b_{\text{priorPE}} = 0.12$ (0.01), $p < .0001$ (see Fig. 4). This suggests that, in addition to uncertainty stemming from unfamiliarity, uncertainty stemming from a recent history of surprising, disappointing experiences prompts

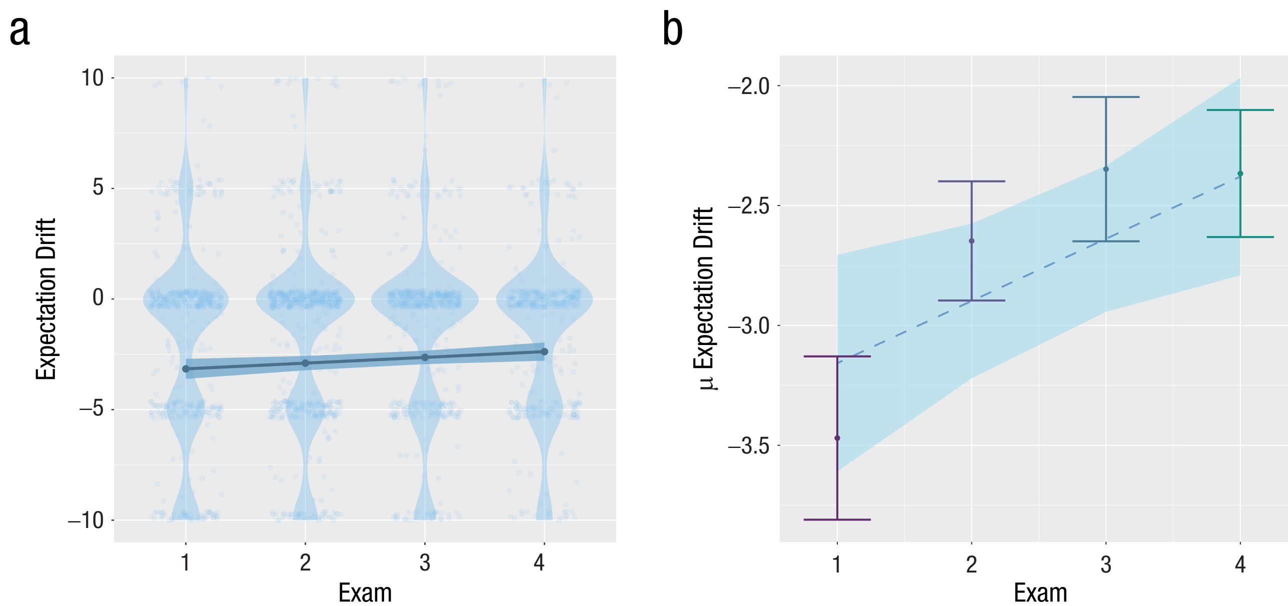

Fig. 3. Decreases in expectation drift with experience. Distributions of expectation drift (a) are depicted across exams. The linear trend indicates that expectation drift between T1 and T2 was predominantly pessimistic but became less pessimistic over time, suggesting that participants reduced their expectations less as they gained experience taking exams. Average expectation drift (b) is plotted over each exam. Pessimistic expectation drift was most pronounced at the first exam (when participants had the least experience with exams) and became progressively less pessimistic over subsequent exams. Shaded regions in (a) and (b) represent 95% confidence intervals surrounding the model-predicted trend of expectation drift across exams, and error bars in (b) represent standard errors of the mean expectation drift for each exam.

pessimistic drift. These results indicate that both a lack of experience and recent disappointments arising from inappropriately optimistic expectations contribute to the uncertainty that drives downward shifts to expectations during waiting periods.

Expectation drift is linked to anticipatory emotion. Next, we evaluated whether expectation drift is driven by people's current affective state as they anticipate an uncertain outcome. Prior work has theorized that current emotional states can drive pessimistic shifts in expectations (Shepperd et al., 1996; Sweeny & Howell, 2017). In support of this hypothesis, we found that anticipatory negative affect (leading up to the reveal of one's grade) predicted pessimistic expectation drift: Participants who experienced greater negative affect prior to receiving their exam grades reduced their expectations more, $b_{\text{antNA}} = -0.02$ (0.01), $p = .01$. This result suggests that pessimistic drift may be an emotion-driven response that is beholden to one's affective state during an uncertain waiting period.

What most strongly predicts pessimistic expectation drift?

To determine the combination of variables that best predict expectation drift, we performed a model comparison over a series of competing models, each with a unique permutation of the predictors examined independently in the above: amount of experience (exam number), subjective uncertainty (confidence rating), recent surprise (prior exam prediction error), and anticipatory negative affect. Baseline negative affect was included as a covariate in models that contained the anticipatory negative affect predictor. Surprisingly, the model that yielded the best fit to the data contained only a single predictor: the prior exam grade prediction error, Akaike's information criterion (AIC) = 11,472.06, Bayesian information criterion (BIC) = 11,499.34 (See Table 2 for all model comparison statistics). To further evaluate which predictor most strongly drove expectation drift, we tested a fully specified mixed-effects model in which we included all predictors simultaneously (anticipatory negative affect, exam number, previous prediction error, confidence). Of the variables in this fully specified model, prior prediction error was the only significant predictor of expectation drift, $b_{\text{priorPE}} = 0.12$ (0.01), $p < .0001$. To refine this model by removing less-impactful variables and further elucidate the most meaningful predictors of expectation drift, we performed a backward elimination of the predictors in our fully specified mixed-effects model using partial F tests. Of the focal predictors, this backward elimination suggested the removal of exam number (model sum of squares accounted for by exam [MSS_{exam}] = 1.0, $F_{\text{exam}}(1, 1217.2) = 0.02$, $p = .88$), followed by confidence rating

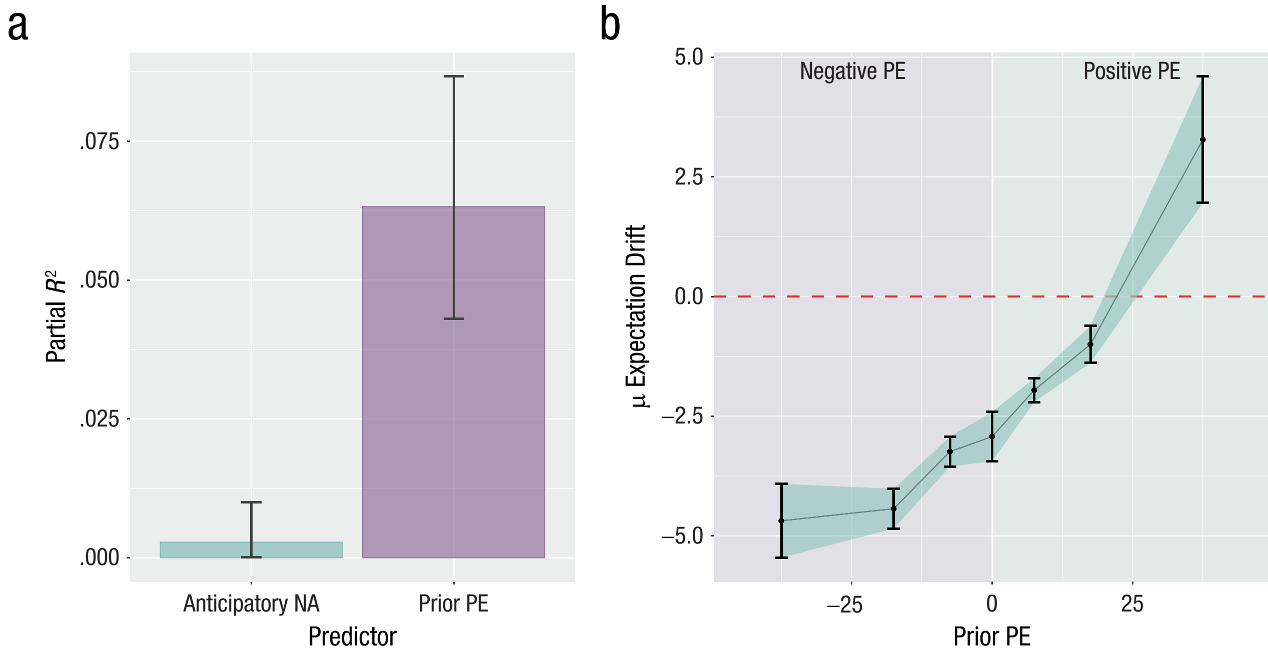

Fig. 4. Expectation drift is preferentially driven by prior prediction errors. Partial R^2 scores for significant predictors of expectation drift are shown in (a). Both anticipatory negative affect and prior prediction error predicted expectation drift, and the effect size for prior prediction error was largest in magnitude, error bars represent 95% confidence intervals for R^2 scores. Average expectation drift (b) is plotted as a function of prediction errors on the preceding exam. Pessimistic expectation drift is largest after experiencing negative prediction errors on the preceding exam; Error bars and shaded regions represent the standard error of the mean. Averages are computed within discrete range of prediction errors: −50 to −25, −25 to −10, −10 to −1, −1 to 1, 1 to 10, 10 to 25, and 25 to 50. Note that standard errors for mean expectation drift following exceedingly large prior prediction errors—see the far left and right sides of (b)—that are somewhat inflated because of the sparseness of observations with large prediction errors. PE = prediction error; NA = negative affect.

($MSS_{confidence}$ = 81.0, $F_{confidence}(1, 1306.7) = 2.03$, $p = .15$) from the fully specified model, indicating that prior prediction error and anticipatory negative affect were better predictors of participants' expectation drift. After removing exam number and confidence from the fully specified model, both prior prediction error, $b_{priorPE}$ = 0.12 (0.01), $p < .0001$, and anticipatory negative affect, b_{antNA} = −0.02 (0.01), $p = .03$, significantly predicted expectation drift (Fig. 4). Overall, prior prediction error exhibited the strongest impact on expectation drift, with an effect size (partial R^2) that was an order of magnitude larger than that of anticipatory negative affect, partial R^2_{antNA} = .003, 95% confidence interval (CI) = [0.000, 0.010]; partial $R^2_{priorPE}$ = .063, 95% CI = [0.043, 0.087].

Consistent with the results from the single-predictor model, predictions from the model refined through backward elimination suggest that individuals who experienced negative prediction errors on the preceding exam were most likely to reduce their expectations when awaiting their grades. This suggests that regardless of how much experience people have accrued, how confident they are in their predictions, or how negative their emotional state is before receiving exam results, the degree to which expectations drift and tend to drift pessimistically depended most strongly on recent unexpected uncertainty—that is, their preceding exam prediction error.

Pessimistic expectation drift transiently and conditionally buffers negative affect

One hypothesis of the function of bracing is that it reduces negative affect caused by goal-relevant outcomes by reducing the likelihood of a negative prediction error (Shepperd et al., 2000; Sweeny & Shepperd, 2010; Taylor & Shepperd, 1998). We tested this by examining the impact of expectation drift—particularly pessimistic drift—on emotional responses. We did this first by averaging over the entire 12-hr period occurring immediately after people saw their exam grades, during which we densely sampled emotion. Controlling for exam-grade prediction errors, which modulate emotional responses, we found that when expectations drifted pessimistically before seeing the exam grade, negative affect was attenuated in the subsequent 12 hrs,

$b_{\text{optimistic-pessimistic}} = 7.18$ (1.09), $p < .0001$. As a follow-up, because prediction errors are known drivers of emotion (Eldar et al., 2018; Rutledge et al., 2014, 2017; Villano et al., 2020), we tested whether pessimistic expectation drift moderated the impact of prediction errors on negative affect. Indeed, pessimistic expectation drift moderated the impact of prediction errors on negative-affect responses over the 12 hrs after seeing one's grade, $b = 0.22$ (0.07), $p = .0013$. This model predicted that negative affect was indeed reduced after expectations shifted pessimistically, but only to a point: when people underperformed their expectations by 9 points or more ($PE \leq -9$), pessimistic drift did not buffer their negative affect (Fig. 5). In contrast, when negative PEs > −9,

Table 1. Regression Results

Independent variables	Estimate	*SE*	*df*	*t*	*p*
In aggregate, expectation drift is predominantly pessimistic					
Expectation Drift ~ 1 + (1 | cohort / *i*)					
(Intercept)	−2.74	0.16	2.03	−17.21	.003
Expectation drift becomes less pessimistic over time (j; exam), as experience accrues					
Expectation Drift ~ *j* + (1 | cohort / *i*)					
(Intercept)	−3.42	0.32	2,692.86	−10.71	< .0001
j	0.26	0.11	2,317.27	2.42	.02
Expectation drift is linked to lower confidence in expectations					
Expectation Drift ~ Confidence + (1 | cohort / *i*)					
(Intercept)	−3.68	0.39	75.48	−9.5	< .0001
Confidence	0.02	0.01	1,811	2.68	.01
Expectation drift is linked to negative PEs on the preceding exam					
Expectation Drift ~ $PE_{j\text{-}1}$ + (1 | cohort / *i*)					
(Intercept)	−2.54	0.19	2.17	−13.34	.00402
$PE_{j\text{-}1}$	0.12	0.01	1,727.42	10.53	< .0001
Expectation drift is linked to increased anticipatory NA					
Expectation Drift ~ Anticipatory NA + (1 | cohort / *i*)					
(Intercept)	−1.94	0.47	617.8	−4.18	< .0001
Anticipatory NA	−0.02	0.01	2,395	−2.51	.01
Baseline NA	−0.01	0.01	614.7	−1.3	.19
Prior PE significantly predicts expectation drift in a fully specified model					
Expectation Drift ~ Exam + Confidence + $PE_{j\text{-}1}$ + Anticipatory NA + NA Baseline + (1 | cohort / *i*)					
(Intercept)	−3.01	0.88	458.9	−3.41	.00072
Exam	0.04	0.20	1,188	0.2	.84
Confidence	0.01	0.01	1,303	1.46	.15
$PE_{j\text{-}1}$	0.12	0.01	1,605	10.4	< .0001
Anticipatory NA	−0.02	0.01	1,723	−1.89	.06
Baseline NA	−0.002	0.01	644	−0.21	.84
Reduced model following removal of exam and confidence					
Expectation Drift ~ $PE_{j\text{-}1}$ + Anticipatory NA + NA Baseline + (1 | cohort / *i*)					
(Intercept)	−2.22	0.52	78.43	−4.26	< .0001
$PE_{j\text{-}1}$	0.12	0.01	1,618.18	10.65	< .0001
Anticipatory NA	−0.02	0.01	1,727	−2.2	.03
Baseline NA	−0.004	0.01	642.41	−0.32	.75
Expectation drift impairs the accuracy of future expectations					
Next accuracy ~ Expectation Drift + *j* + $Accuracy_j$ + (1 | cohort / *i*)					
(Intercept)	76.7	2.13	116.6	36.03	< .0001
Expectation Drift	0.09	0.03	1,756	2.93	.003
j	0.69	0.23	1,023	3.06	.002
$Accuracy_j$	0.14	0.02	1,730	6.07	< .0001

(continued)

Table 1. *(continued)*

Expectation drift moderates NA responses to exam-grade PEs					
Independent variables	Estimate	*SE*	*df*	*t*	*p*
12-hr Average NA					
(Intercept)	1.04	0.92	2.60	1.14	.35
Drift direction	6.41	1.12	1,462.35	5.74	< .0001
PE	−0.57	0.04	1,437.86	−15.52	< .0001
Drift direction: PE	0.22	0.07	1,455.30	3.23	.0013
Initial reactivity (first hour only)					
(Intercept)	3.39	1.68	2.28	2.01	.17
Drift direction	10.54	1.50	1,326.80	7.01	< .0001
PE	−0.90	0.05	1,330.30	−18.08	< .0001
Drift direction: PE	0.20	0.09	1,322.28	2.23	.026
Late-Phase Reactivity (Hours 8–12)					
(Intercept)	−1.11	1.27	2.15	−0.88	.47
Drift direction	3.10	1.55	1,008.63	2.0	.045
PE	−0.36	0.05	979.51	−7.22	< .0001
Drift direction: PE	0.26	0.09	1,003.88	2.73	.0064

pessimistic drift significantly attenuated negative affect. This suggests that over the entire 12-hr period, pessimistic expectation drift effectively buffered negative-affect responses to small negative prediction errors but not to larger negative prediction errors.

We followed up this analysis by examining for how long pessimistic shifts in expectation buffered negative-affect responses to small negative prediction errors. Were the beneficial emotional consequences of pessimistic expectation shifts persistent across the full 12-hr period, or were they more transient, lasting only an hour or so? To determine whether this negative-affect buffering effect varied in effectiveness over time, we separately examined the emotional response in the first hour (hours 0–1) after seeing one's grade and the final 4 hrs after seeing one's grade (hours 8–12). Indeed, pessimistic

Table 2. Model Comparisons

Model number	Predictor variables	Number of parameters	AIC	BIC
Models Predicting Expectation Drift				
3	$PE_{j\text{-}1}$	5	11,472.06	11,499.34
8	Confidence + $PE_{j\text{-}1}$	6	11,471.58	11,504.31
6	Exam + $PE_{j\text{-}1}$	6	11,473.85	11,506.58
10	$PE_{j\text{-}1}$ + Anticipatory NA + Baseline NA	7	11,471.68	11,509.87
11	Exam + Confidence + $PE_{j\text{-}1}$	7	11,473.38	11,511.57
14	Confidence + $PE_{j\text{-}1}$ + Anticipatory NA + Baseline NA	8	11,471.65	11,515.30
13	Exam + $PE_{j\text{-}1}$ + Anticipatory NA + Baseline NA	8	11,473.66	11,517.30
15	Exam + Confidence + $PE_{j\text{-}1}$ + Anticipatory NA + Baseline NA	9	11,473.63	11,522.73
2	Confidence	5	11,573.64	11,600.92
1	Exam	5	11,577.35	11,604.63
5	Exam + Confidence	6	11,575.02	11,607.76
4	Anticipatory NA + Baseline NA	6	11,577.15	11,609.88
9	Confidence + Anticipatory NA + Baseline NA	7	11,575.28	11,613.47
7	Exam + Anticipatory NA + Baseline NA	7	11,578.83	11,617.02
12	Exam + Confidence + Anticipatory NA + Baseline NA	8	11,576.95	11,620.59
Models Predicting Accuracy at Next Exam ($Accuracy_{j+1}$)				
3	Expectation Drift + Exam + $Accuracy_j$	7	12,688	12,726
2	Expectation Drift + Exam	6	12,704	12,737
1	Expectation Drift	5	12,716	12,744

Note: PE = prediction error; NA = negative affect; AIC = Akaike's information criterion; BIC = Bayesian information criterion.

expectation drift moderated participants' initial negative-affect responses to prediction errors (Fig. 5) in the first hour after seeing their grade, $b = 0.20$ (0.09), $p = .026$, as well as their longer-term negative affect in the latter hours of the sampling period 8 to 12 hrs after seeing their grade, $b = 0.26$ (0.09), $p = .0064$. Examining the predicted patterns from these models added nuance to the findings, however. Within the first hour of seeing their exam grade, pessimistic drift buffered negative-affect responses when people underperformed their expectations by 11 points or less (PE ≥ -11; Fig. 5). However, beyond the first hour, pessimistic drift quickly became ineffective at buffering negative affect, particularly if someone had received disappointing news (a negative prediction error). That is, as time passed beyond the first hour, the emotion-buffering effect of pessimistically shifting expectations evaporated if participants had received a grade that fell below their expectation. In fact, during the final 4 hrs of the burst-sampling period, model predictions indicated that pessimistic drift reduced negative-affect responses only when someone had received a positive prediction error. Thus, pessimistic drift appeared to provide no emotional benefit when prediction errors were below zero. This suggests that pessimistic drift sweetens the emotional effects of positive surprises for up to 12 hrs, but primarily buffers initial negative-affect responses to moderately disappointing outcomes (i.e., negative prediction errors) and provides no clear benefit for larger negative upsets (i.e., negative prediction errors larger than −11 in magnitude). In sum, pessimistic drift produces affective benefits relative to optimistic drift, but by and large only briefly, and fails to mitigate the emotional impact of highly unexpected and disappointing (i.e., worst-case) upsets.

Pessimistic expectation drift impedes prediction-error-driven learning

When an outcome conflicts with one's expectations, prediction errors inform how to update expectations for similar situations in the future (Rescorla & Wagner, 1972; Sutton & Barto, 1998). Prediction-error-driven learning improves the accuracy of one's future expectations, which reduces uncertainty. Yet an untested side effect of expectation drift is that it may alter prediction errors in a manner that renders them less useful in learning. We hypothesized that expectation drift would alter the fidelity of prediction errors as learning signals, imbuing them with noise and leading to less accurate future expectations. Indeed, pessimistic drift was linked to reduced expectation accuracy at the next exam, $b_{\text{expectationdrift}} = 0.09$ (0.03), $p = .003$ (Fig. 6). Thus, although pessimistic drift may minimize negative emotion in the immediate aftermath of receiving an uncertain outcome, lowering expectations to avoid unexpected disappointment may ultimately limit how much one is able to learn from those events (i.e., prediction errors). A consequence of this is that pessimistic expectation drift may counterintuitively sustain the degree of uncertainty surrounding future outcomes by reducing the fidelity of prediction errors, even as people accrue experience. Paradoxically, this may lead people to continue to lower their expectations over time, as uncertainty stemming from prediction errors appears to have an outsized influence on pessimistic expectation drift.

Discussion

Do our expectations shift as news of important events draws near? Cross-sectional evidence suggests that individuals adopt pessimistic expectations, bracing themselves for the worst before uncertain outcomes are revealed. This possibility is often not accounted for in computational models of learning and decision-making, which tend to assume that expectations are stable while people wait for the outcomes of uncertain events. Determining whether expectations indeed drift is important because drifting expectations change the set point for prediction errors, altering prediction errors in a manner that could drive variability in the way individuals respond to, and learn from, surprising events. As computational approaches seek to characterize the bases of learning and emotion, a crucial step requires understanding whether expectations change during anticipation.

Here, in a high-stakes, goal-relevant, real-world setting, we refine current accounts of whether expectations shift, and we clarify their causes and consequences. Using repeated-measures EMA, we found that people's expectations are not static, as typically assumed in computational models, but often drift as important news draws near. Moreover, when expectations do drift, they tend to drift pessimistically, in line with previous accounts of bracing (Shepperd et al., 2000; Sweeny & Krizan, 2013; Taylor & Shepperd, 1998). Further, our prospective, repeated-measures design enabled us to identify the factors that drive pessimistic expectation drift. Although prior work has held that individuals brace to avoid disappointment, to mobilize resources, and to employ magical thinking (Carroll et al., 2006; Sweeny et al., 2006), we found that people reduce their expectations less as they gain experience with exams, indicating that expectation drift is not a general, stable response during anticipation of goal-relevant outcomes, but rather a dynamic behavior that tracks the current degree of uncertainty. Specifically, pessimistic expectation drift did not simply result from a lack of experience

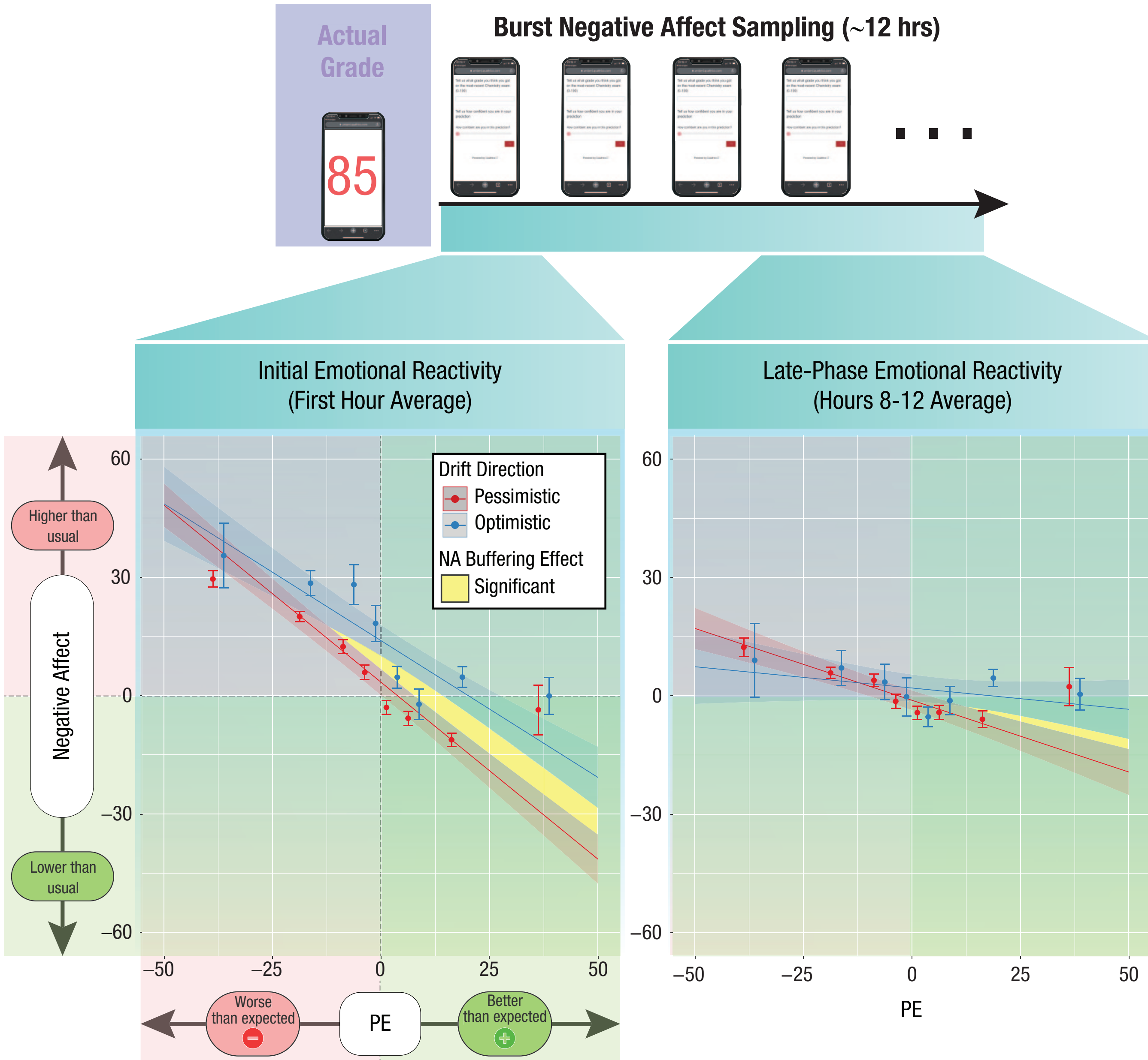

Fig. 5. Pessimistic expectation drift transiently buffers the negative affective impact of negative prediction errors. Baseline-corrected negative-affect responses to exam grades are plotted for participants whose expectations drifted pessimistically (in red) and for participants whose expectations drifted optimistically (in blue) as a function of prediction error. Slopes represent model-predicted effects, whereas points with error bars represent negative-affect scores from raw data, averaged within different levels of prediction error (red points represent averages for pessimistic drift, and blue points represent averages for optimistic drift). At left, we show the initial reactivity of negative affect (first hour); at right, we show the last four hours (hours 8–12) of negative affect. Regions highlighted in yellow (i.e., above −11 on the *x*-axis for the left side, and above 13 on the right side) demarcate levels of predication error in which pessimistic drift yielded a significant reduction in negative affect, relative to optimistic drift. Thus, in the first hour after receiving a grade, pessimistic drift yielded a significant reduction in negative affect for negative prediction errors smaller than or equal to −11, and for positive prediction errors as well. In the late phases of the sampling period (hours 8–12), pessimistic drift yielded a significant reduction in negative affect for positive prediction errors that were greater than or equal to 13. Although statistical models suggest that pessimistic drift significantly moderated average negative-affect responses to prediction errors in both initial and late phases of the burst-sampling period, the emotional benefits of pessimistic drift were concentrated within the first hour after grades were revealed and were specific to small negative prediction errors. Pessimistic drift did not buffer the emotional impact of negative prediction errors in the late phases of emotional reactions after the grade reveal (right). These data suggest that in aggregate, pessimistic drift buffers initial negative-affect responses to small (but not large) negative prediction errors and does little to alter persistent emotional responses to negative prediction errors. Error ribbons around slopes represent 95% confidence intervals around predicted conditional effects. Points in both sides of the figure represent mean negative-affect scores over a discrete range of prediction errors, and error bars represent standard errors of the mean. Discrete prediction error ranges on each panel are −50 to −25, −25 to −10, −10 to −5, and −5 to 0, with identical ranges for positive prediction errors. PE = prediction error; NA = negative affect.

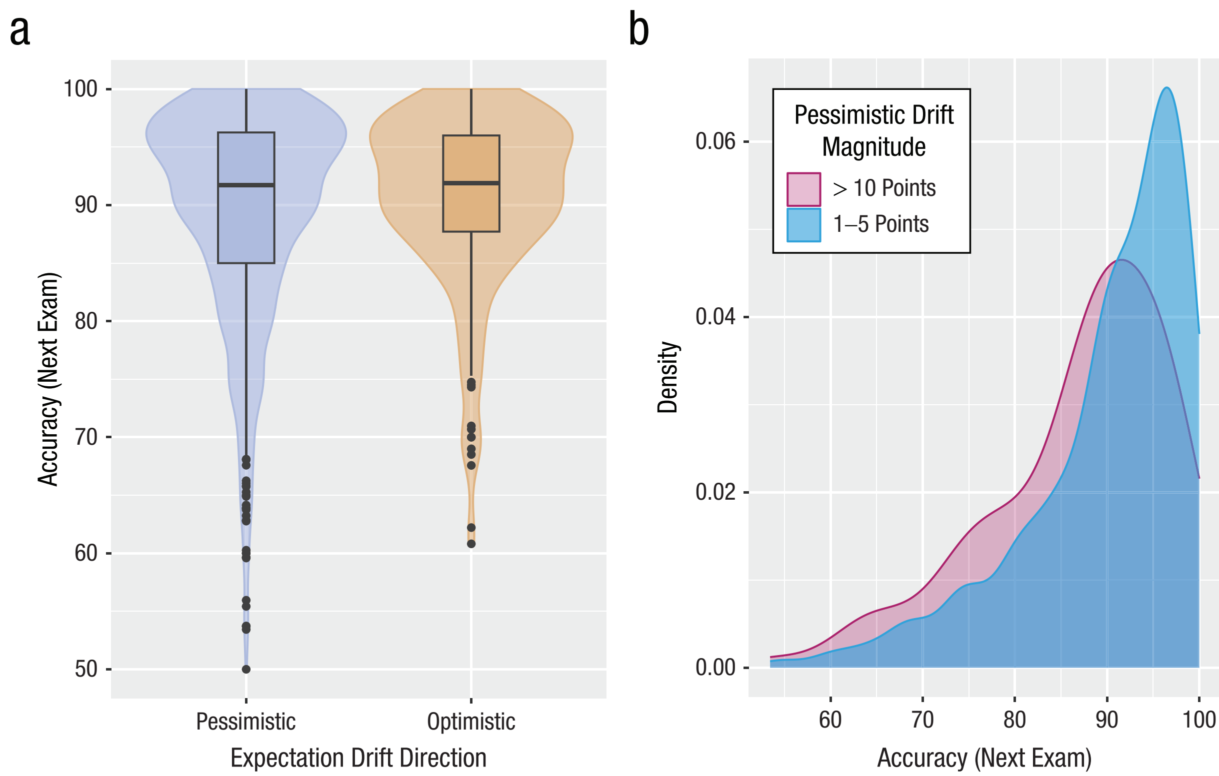

Fig. 6. Pessimistic expectation drift impedes prediction-error-driven learning, leading to less accurate future expectations. Distributions of expectation accuracy at the next exam (a) are plotted for people who reported pessimistic expectation drift (purple violin) and for participants who reported positive expectation drift. Pessimistic expectation drift is linked to poorer expectation accuracy, indicating that bracing may alter prediction errors in a manner that impedes one's ability to accurately update expectations for the future. Distributions of expectation accuracy at the next exam (b) are plotted for participants whose expectations drifted between 1 and 5 points (on a 100-point grade scale), and for participants whose expectations drifted by more than 10 points. For participants who lowered their expectations, larger magnitudes of expectation drift were linked to less accurate expectations at the next exam.

with an event, but was primarily dependent on how inaccurate one's recent expectations were. This finding corroborates at least one qualitative study suggesting that individuals with a history of recurrent miscarriages (likely negative prediction errors) were more likely to brace for upsets during future pregnancies (Ockhuijsen et al., 2013). It is important to note that the present study is the first to empirically test and quantify the relationship between prediction errors and expectation drift over time, and this finding suggests that pessimistic drift—and thus bracing—is not just a preemptive response to the possibility of future disappointment but, critically, is a response to uncertainty arising from unpredictable prior experiences and disappointment stemming from misplaced optimism.

Prior work suggests that pessimistic expectation drift confers emotional benefits by increasing the probability of a positive prediction error (Sweeny et al., 2016; Sweeny & Falkenstein, 2017; Sweeny & Krizan, 2013). By using time-locked, repeated-measures EMA, we were able to explore more deeply how expectation drift altered the fine-scale temporal dynamics of emotional responses to unexpected exam grades, from the precise moment participants viewed their grades through the ensuing 12 hrs. As has been suggested (Shepperd et al., 2000; Sweeny & Falkenstein, 2017; Sweeny & Shepperd, 2010; Taylor & Shepperd, 1998), we found that bracing does buffer negative emotional responses to unexpectedly negative outcomes. However, it appeared that the strength of this buffering effect varied both over time and with the magnitude of one's exam-grade prediction error. Although pessimistic drift buffered participants' initial affective responses to negative prediction errors that were smaller than −12 in magnitude, it had little to no buffering effect for larger negative prediction errors. Furthermore, the beneficial emotional impact of bracing was fleeting. The putative beneficial effects of pessimistic drift on emotional responses to negative prediction errors were not present after several hours had elapsed. Taken together, our results suggest that refinements are needed to the broad hypothesis that bracing buffers the emotional impact of events. Our data suggest that lowering one's expectation during a waiting period is not a uniformly effective emotion-regulation strategy. Moreover, when it is effective, the benefits of pessimistic expectation drift are primarily limited to the initial moments of emotional reactivity. Therefore, pessimistic expectation drift may offer some short-term relief from minor to moderate upsets but does little to mitigate the emotional impact of severely upsetting outcomes.

Given that pessimistic expectation drift produced a short-term emotional-buffering effect over a (somewhat narrow) range of negative prediction errors, one might conclude that pessimistic expectation drift is broadly adaptive. However, we found that pessimistic expectation drift hinders learning from prediction errors. Specifically, the more people lowered their expectations, the less accurate their future expectations were. Thus, it appears that short-term attempts to manage uncertainty via shifting expectations pessimistically can perpetuate longer-term uncertainty. We hypothesize that the increased long-term uncertainty associated with expectation drift stems from the addition of noise to people's expectations, which makes it more difficult for them to effectively attribute the precise source of the prediction error; this in turn impedes their ability to appropriately update future expectations.

Although these results clarify our understanding of both the causes and consequences of expectation drift, there are several limitations of this work that should be addressed in future studies. First, given that some of these data were collected after COVID-19 was declared a public health emergency, future work should confirm that our findings generalize beyond the time frame of the COVID-19 pandemic—a time when daily emotional dynamics were profoundly altered for many individuals (Reneau et al., 2024). Second, because we did not measure expectations at more than two time points, we were unable to determine the precise moment when expectations drifted—for instance, whether expectations shifted downward a few hours after an exam, or immediately before the moment of truth, when bracing is typically thought to occur (Shepperd et al., 2000; Sweeny & Howell, 2017; Taylor & Shepperd, 1998). Future research should replicate these methods with more frequent samples of expectations throughout the waiting period to better understand what causes expectations to shift and when. Third, although we aimed to evaluate the influence of anticipatory emotion and factors related to uncertainty (e.g., familiarity with events, a recent history of unexpected outcomes), we did not measure other factors thought to drive pessimistic shifts in expectations. Beyond efforts to actively mitigate disappointment, it may be that participants in our sample lowered their expectations for reasons related to magical thinking or to mobilize resources to preemptively manage an impending upset, as some other work suggests (Carroll et al., 2006; Sweeny et al., 2006). Thus, in addition to confirming the role of uncertainty and anticipatory emotion as moderators of expectation drift, future studies should also evaluate the influence of magical thinking and preemptive preparatory efforts on expectation trajectories during waiting periods. Fourth, it is possible that some of the pessimistic expectation drift we observed could be because participants were gaining more information about their likely grades (e.g., by comparing answers with peers). However, we think this is unlikely because expectations tended to drift pessimistically, not uniformly, in our data, suggesting that above and beyond the effects of new information, individuals often brace for disappointment when feedback is imminent. Last, it is possible that participants differed in their motivations for how they formed their expectations: For example, some might prioritize forming accurate expectations, and others might prioritize the avoidance of disappointment, and brace pessimistically as a result. Future work should aim to evaluate individual differences in how participants form their expectations. Indeed, if some participants are less interested in accuracy, the learning deficits associated with pessimistic drift may not be an unintended consequence as we have presumed but rather an expected trade-off for individuals intent on avoiding disappointing surprises.

In conclusion, although lowering expectations during waiting periods may yield affective benefits, this strategy appears largely ineffective for mitigating the emotional impact of putative worst-case scenarios and unexpected negative outcomes. More broadly, by impeding prediction-error-based learning, pessimistic expectation drift may counterintuitively lead to sustained uncertainty in expectations as future events come to pass. Thus, a more pertinent question for future investigations is not whether bracing is emotionally adaptive but whether its consequences for long-term uncertainty management outweigh its short-term emotional benefits.

Transparency

Action Editor: Daniela Schiller
Editor: Patricia J. Bauer
Author Contributions

William J. Villano: Conceptualization; Data curation; Formal analysis; Investigation; Methodology; Project administration; Resources; Software; Validation; Visualization; Writing – original draft; Writing – review & editing.

Noah I. Kraus: Data curation; Investigation; Methodology; Resources; Software; Writing – review & editing.

Travis R. Reneau: Data curation; Investigation; Methodology; Resources; Software; Writing – review & editing.

Brittany A. Jaso: Data curation; Investigation; Methodology; Resources; Software; Writing – review & editing.

A. Ross Otto: Conceptualization; Methodology; Supervision; Writing – original draft; Writing – review & editing.

Aaron S. Heller: Conceptualization; Formal analysis; Funding acquisition; Investigation; Methodology; Project administration; Resources; Supervision; Validation; Writing – original draft; Writing – review & editing.

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Open Practices Statement

All data needed to evaluate the conclusions in the article are present in the article or in the Supplemental Material available online. Data and analysis code are available upon reasonable request to the authors. The present study was not preregistered.

ORCID iDs

Travis R. Reneau https://orcid.org/0000-0002-0211-2482
A. Ross Otto https://orcid.org/0000-0002-9997-1901
Aaron S. Heller https://orcid.org/0000-0002-0680-3248

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