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BRIEF REPORT

Increased attention towards progress information near a goal state

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Abstract
A growing body of evidence across psychology suggests that (cognitive) effort exertion increases in proximity to a goal state. For instance, previous work has shown that participants respond more quickly, but not less accurately, when they near a goal—as indicated by a filling progress bar. Yet it remains unclear *when* over the course of a cognitively demanding task do people monitor progress information: Do they continuously monitor their goal progress over the course of a task, or attend more frequently to it as they near their goal? To answer this question, we used eye-tracking to examine trial-by-trial changes in progress monitoring as participants completed blocks of an attentionally demanding oddball task. Replicating past work, we found that participants increased cognitive effort exertion near a goal, as evinced by an increase in correct responses per second. More interestingly, we found that the rate at which participants attended to goal progress information—operationalized here as the frequency of gazes towards a progress bar—increased steeply near a goal state. In other words, participants extracted information from the progress bar at a higher rate when goals were proximal (versus distal). In exploratory analysis of tonic pupil diameter, we also found that tonic pupil size increased sharply as participants approached a goal state, mirroring the pattern of gaze. These results support the view that people attend to progress information more as they approach a goal.

Keywords Cognitive and attentional control · Eye movements and visual attention

Introduction

In daily life, we routinely face activities that can only be completed through the sustained investment of cognitive effort—for example, finishing a work shift, completing a difficult video game, or maintaining multiple online conversations at once. At the same time, a large body of evidence over the past decade suggests that people find it difficult to sustain exertion of cognitive effort over long periods of time (Inzlicht et al., 2014; Kurzban, 2016; Lin et al., 2020; Massar et al., 2016; Matthews et al., 2023; Umemoto et al., 2019; Wiehler et al., 2022) and doing so for extended periods of time leaves people fatigued and/or disengaged (Ackerman, 2011; Francis et al., 2018; Lorist et al., 2000; Milyavskaya et al., 2019; Wiehler et al., 2022).

At the same time, both recent and classic work demonstrate that people and animals tend to increase effort exertion near a goal. First formalized in the 1930s, Hull's (1932) *goal-gradient hypothesis* posits that animals increase their movement vigour as their distance to a goal decreases (confirmed experimentally by Brown, 1948). Extending this idea to human behaviour, researchers have observed that goal gradients manifest in a variety of domains of human behaviour from sports performance (McGibbon et al., 2018; Tucker et al., 2006) and consumer choice (Cheema & Bagchi, 2011) to cognitive control (Devine & Otto, 2022; Devine et al., 2024; Emanuel et al., 2022; Katzir et al., 2020), finding that across domains, effort exertion increases near a goal.

To this end, Devine et al. (2024) recently provided an initial empirical demonstration of goal-gradient like effects manifesting in cognitive tasks requiring sustained attention. There, participants completed several blocks of a simple "oddball" task where, critically, information about their progress through a block—which could only be advanced by making rapid but correct responses—was represented by a visually presented progress bar that appeared at the top of the task display. They observed that participants responded more quickly without sacrificing accuracy (a signature of cognitive effort intensification) when participants were close to completing a block of trials—that is, when the progress bar was nearly full. This marked uptick in response speed

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(and to a lesser extent, accuracy) was taken to suggest that goal gradient effects in cognitive effort, operationalized as faster and/or more correct responding in proximity to a goal, are readily observable in the context of a simple cognitive task requiring continuous attention.

However, several questions remain open about the mechanisms giving rise to the goal-gradient effects observed by Devine et al. (2024). For example, when progress information is available during a block, when are individuals most likely to monitor goal progress information? Establishing an understanding of the attentional dynamics of progress monitoring would be an important first step in understanding the computations underpinning goal-gradient effects in cognitive effort exertion. Here, we used eye-tracking to expand our investigation of goal-gradient effects in cognitive effort to examine two distinct hypotheses about the time course of progress information monitoring.

One possibility is that individuals may monitor progress information to reduce their uncertainty with respect to task progress (Devine & Otto, 2022), which we call the uncertainty hypothesis (Gottlieb & Oudeyer, 2018). On this view, individuals would periodically monitor task progress, updating their representation of their goal proximity as a function of their uncertainty with respect to goal proximity—for example, when sufficient time has elapsed since they last monitored their task progress. This sort of monitoring strategy would give rise to the observed goal-gradient effects in performance if individuals increase their effort investment when block progress surpasses a certain threshold (e.g., 75%) This account therefore assumes that progress monitoring and cognitive control are mobilized separately during goal pursuit, monitoring being deployed prior to adaptations in cognitive control and informing subsequent control allocation. This view predicts that an individual's rate of progress monitoring should be uniform when progress information is available throughout a task block—that is, individuals should be equally likely to attend to block progress information at every point in a task block.

Alternatively, an individual's rate of progress monitoring could depend on their goal proximity—for instance, people may attend to progress information more near the end of a demanding task because goal progress is more salient. We call this view the salience hypothesis. This hypothesis would predict that progress monitoring and performance both increase as a function of proximity of a goal. This proposal dovetails well with a recent body of research finding that reward-predicting and task goal-related stimuli exert powerful attentional capture effects (Mine & Saiki, 2018). Thus, the salience account predicts that an individual's rate of monitoring progress information should increase as they approach the goal, mirroring the goal-gradient effect we previously observed in task performance (Devine et al., 2024).

In order to adjudicate between these two possibilities—whether progress monitoring is equally likely over the course of a block (the uncertainty hypothesis), or progress monitoring increases with proximity to the goal (the salience hypothesis)— we used eye-tracking to examine trial-by-trial changes in progress monitoring as participants completed blocks of an attentionally demanding oddball task (Beierholm et al., 2013; Devine et al., 2024; see Fig. 1), which

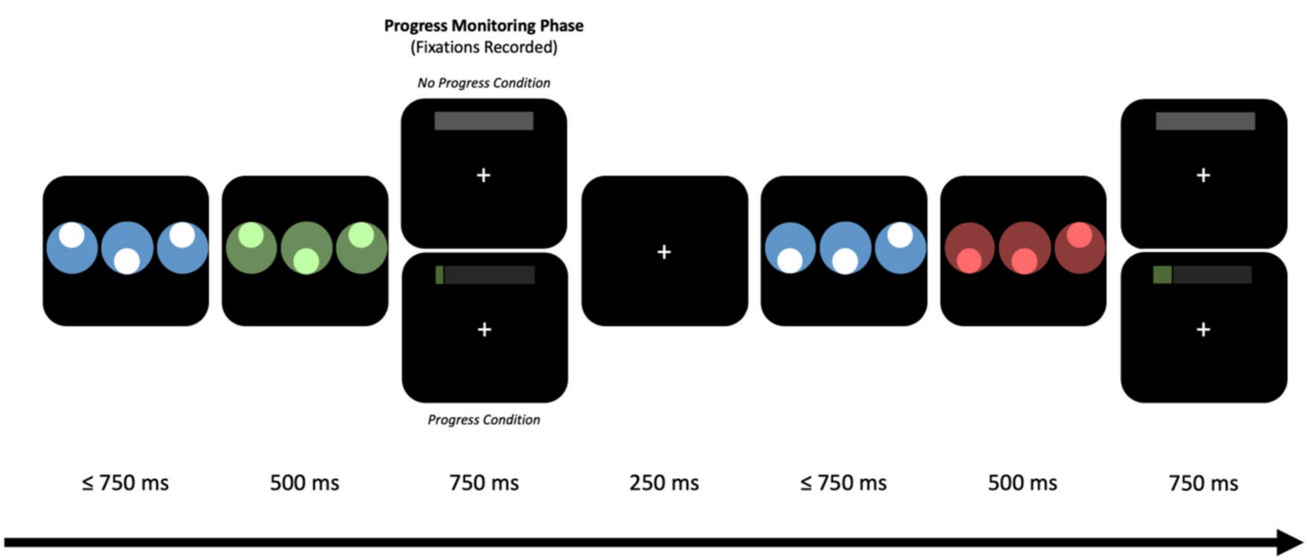

Fig. 1 Schematic of the oddball task. Participants were asked to judge which of three shapes was the "odd one out," within 750 ms. In the progress condition, a green progress bar incrementing after each correct response, until the required number of correct responses were given. In the no-progress condition, this progress bar was replaced with a greyed-out (but otherwise visually identical) bar. (Colour figure online)

necessitates sustained attention to make a series of rapid (subsecond) and accurate judgements about which of three stimuli presented on the screen is the "odd one out." Critically, between trials, participants were presented with a bar representing their goal progress (i.e., the number of remaining correct responses needed to complete a block), which required that participants fixate to a region separate from the oddball stimuli. Doing so, we directly examine when (and how frequently) individuals attend to progress information—operationalized here as fixations towards a progress bar—as a function of goal proximity. Taking this approach, we could also assess the replicability of the goal-gradient effects we recently observed in performance in the oddball task (Devine et al., 2024). Finally, the eye-tracking methodology employed here also permits an exploratory examination of variation in tonic pupil diameter with respect to goal proximity, which has been previously linked to changes in attentional control states (van den Brink et al., 2016; Unsworth & Robison, 2016).

Method

Participants

To estimate an appropriate target sample size, we conducted a simulation-based power analysis (Arend & Schäfer, 2019), in which participant behaviour consistent with our hypotheses was simulated on the oddball task (described below). This a priori power analysis revealed that 78 participants would yield 90% power to detect effect sizes of minimal interest (see the Supplemental Materials for full details of the power analysis). Accordingly, we recruited 88 healthy adult participants from McGill University's participant pool. Seven participants experienced technical issues with the eye tracker that precluded data recording, leaving 81 participants in the final analysis (average age = 21.60 years, *SD* = 6.09, 60 women, 20 men, one other). All participants gave informed consent prior to testing and were compensated with course credit or monetary compensation. This procedure was approved by the McGill Research Ethics Board.

Oddball task

Our task designed followed Devine et al. (2024), which was based on Beierholm et al.'s (2013) oddball task. On each trial, participants were shown three blue circles (154 px in diameter) that were evenly spaced horizontally across the screen (256 px apart). Two of these circles were identical, containing an inner white circle at the top (bottom) of the blue circles, while the third was different, containing a white circle at the bottom (top) of the blue circles (see Fig. 1). Participants were asked to identify which shape was the "odd one out" using the Q (leftmost circle), W (middle circle), or E (rightmost circle) keys to indicate their choice. The position of the odd circle was randomized each trial. On 90% of trials, participants had up to 750 ms to indicate which stimulus was the "odd one out," but 10% of trials had a stricter deadline of 600 ms to maintain participants' attention.

After responding, participants were presented with feedback indicating whether they correctly identified the oddball stimulus or not, in which case all three stimuli turned green or red, respectively. If they failed to respond within the response deadline, the three stimuli turned grey. Feedback remained on the screen for 500 ms.

After receiving feedback, participants proceeded to the progress monitoring phase of the trial. Here, a fixation cross (154 px) was shown in the centre of the screen, and above the fixation cross a progress bar was displayed in the upper portion of the screen (y-coordinate = 614 px). The progress bar was 922-px long and 307-px wide, which informed by previous pilot testing suggesting that participants could not clearly view the progress bar while foveating the fixation cross. Importantly, we employed a gaze-contingent display to ensure that participants needed to make fixations towards the progress bar to obtain progress information. Specifically, we defined an area of interest (AOI) to identify fixations to the progress bar, whose size and position was identical to the progress bar itself. When a participant made a fixation to this AOI, the progress bar appeared, and if they subsequently fixated outside of this AOI, the progress bar would disappear. The progress bar would not reappear for the remainder of the monitoring phase, even if they fixated to the AOI again, to avoid multiple fixations within the same trial. This progress monitoring phase lasted 750 ms. An intertrial interval (ITI) of 250 ms then followed the progress monitoring phase, after which the next trial began.

Procedure

Participants were seated comfortably in front of a 24-in. monitor, set to a resolution of 1,280 × 1,024 px in a dimly lit room. Participants were instructed to keep their heads still on a chin mount positioned 60 centimetres from the display. During the oddball task, participants' right pupil diameter and fixations were measured using an EyeLink 1000 eye-tracker (SR Research, Osgoode, ON) set to a sampling rate of 1000 Hz. Stimuli were presented using the PsychoPy Python library (Peirce, 2007), synchronized with the eye-tracker. Prior to the experiment, participants underwent a standard 9-point calibration procedure and a practice phase on the oddball task. There were three blocks of practice trials: 1) the oddball task alone (five correct responses needed to progress); 2) practice looking at the progress bar (i.e., first fixate at the cross, and go up look at the rectangle border of the progress bar) (20 successful fixations at the bar needed to progress); and 3) task + progress bar, mimicking the full task (15 correct responses needed).

After completing the practice phase, participants completed two types of oddball task blocks—progress blocks and no-progress blocks. In progress blocks, fixations to the progress bar during the progress sampling phase revealed a green bar that was filled proportionally to the number of correct responses the participant had provided in that block (i.e., the number of correctly identified oddball stimuli; Fig. 1). For example, if the participant had correctly responded on 15 trials and the number required to finish the block was 30, then the bar would be half filled with green. In no-progress blocks, fixations towards the progress bar during the progress sampling phase revealed a solid grey bar that did not convey any progress information but was otherwise visually identical to the bar in the progress blocks (i.e., same width, height, and background colour; Fig. 1). These blocks were included as a control condition to ensure that the observed dynamics gaze behaviour reflected participants' monitoring of progress. In both progress and no-progress blocks, to complete a block, a participant needed to correctly identify the odd shape out for a predefined, pseudorandomized number of stimuli (i.e., trials). The number of correct responses required on a given block was drawn from a uniform distribution with bounds between 25 and 35. Participants completed 16 blocks (~550 trials per participant) of the oddball task, repeating each progress condition eight times in a pseudorandomized order. Participants were not informed about the total number of blocks of trials they were required to complete.

Behavioural data analysis

To analyse goal-gradient effects jointly across RTs and accuracy rates, we computed efficiency scores (ES) across conditions and goal proximity, where $ES = \frac{P(Correct)}{\frac{1}{N}\sum RT}$, reflecting the number of correct responses per second (also known as the Rate Correct Score; Vandierendonck, 2017). We chose $N = 6$ in this case, to reflect six bins of proximity (0, 0.2, 0.4, 0.6, 0.8, 1.0). Higher scores are taken to indicate higher efficiency. Statistically, we estimated mixed-effects regressions predicting participants' ES from progress information condition (deviance coded, −0.5 = no-progress, 0.5 = progress), goal proximity (distance to the end a block, mean-centred), and block number (mean-centred). As we have previously observed that goal gradient effects in cognitive tasks are characterized by a precipitous decrease in performance after the start of a block uptick and a sharp uptick in performance sharply near the end of a block (Devine et al., 2024), we captured this potential pattern in our model using linear and a quadratic terms representing goal proximity (hereafter *proximity*^{2}; computed as the square of the goal proximity term). Larger coefficients of the *proximity*^{2} indicate a steeper increase in performance near the end of a task.

Supporting these analyses, we estimated mixed-effects regressions predicting participants' log-transformed RTs on correct trials, and accuracy (using a logistic model) from the same predictors. Results from these analysis mirror those of ES and are reported in the Supplemental Materials (Table S2 and Fig. S2).

All models were estimated in a Bayesian framework using the *brms* package for R (Bürkner, 2017). Random effects were estimated for all predictor variables unless they caused convergence issues or random variance posteriors were very near zero. All reported coefficients (b) are median posterior values, credible intervals (CI; i.e., highest density intervals) are at the 95% level, and Bayesian *p* values (P) represent one minus the proportion of the posterior that falls above or below zero (depending on the sign of the median posterior value: below zero if b < 0 and above if b > 0). In line with the traditional interpretation of frequentist *p* values, Bayesian *p* values can be interpreted probabilistically as "there is a (P $\times$ 100) percent chance that the effect is zero or a reversal of the central tendency." All models were fit across four chains with 5,000 iterations each, discarding the first 2,000 samples of each chain for burn-in.

Gaze analysis

To examine how participants' patterns of gaze towards the progress bar varied as a function of progress condition and goal proximity, we analysed trial-to-trial fixations to the AOI containing the progress bar. Owing to the gaze-contingent display procedure described above, as participants could only view the progress bar once within the trial. If a participant's gaze overlapped with this region at any point during the progress monitoring phase, the trial was labelled as a "gaze" trial; otherwise, it was labelled as a "no-gaze" trial. Statistically, we estimated a Bayesian mixed-effects logistic regression to predict these fixations towards the progress bar during the progress sampling phase from progress information condition, goal proximity, proximity^2, and block number.

Tonic pupil diameter analysis

It is important to note that the present experiment was not initially designed with the analysis of pupil data in mind. As the timing of experiment events precluded temporal isolation of task-evoked pupillary responses and the luminance of stimuli were not controlled (Peysakhovich et al., 2017), our design precludes the analysis of phasic (i.e., rapid, task-evoked) pupil responses. However, the design still permitted analysis of slow variations in pupil diameter (i.e., tonic pupil diameter), separately analysed within progress and no-progress blocks to avoid issues stemming from differences in luminance across the two conditions.

Pupil diameter data were first preprocessed using the "pypillometry" library for Python (Mittner, 2020), to identify and interpolate eye blinks. Then, we extracted tonic pupillary activity—corresponding to the slow-varying change in baseline pupil diameter over the course of a block of trials. To estimate trial-level tonic pupil diameter, we applied a low-pass filter with a 0.01-Hz cutoff to the preprocessed pupil data, down-sampled the signal to 50 Hz, and *z*-scored this measure within subjects. We took the average of this standardized tonic pupil diameter over the course of an oddball trial as a trial-by-trial summary measure of tonic pupil activity. Following our analysis of task performance, we estimated Bayesian mixed-effect regressions to predict trial-level tonic pupil size from progress information condition, goal proximity, proximity^2, and block number.

Results

Task performance

Overall, participants' RTs were fast (mean = 549.52), taking on average 73% of the allotted time (750 ms) to respond, as well as accurate (P(Correct) = 0.93). Following our previous study, we hypothesized that participants would exhibit speeded responses, with sustained accuracy rates near a goal (i.e., the end of a block), but only in the progress condition where participants were provided with information about task progress (Devine et al. 2024). We quantified performance using efficiency scores, which yield a measure of correct responses per second (see Methods). These results are summarized in Fig. 2, which depict participants' efficiency scores as a function of progress condition and goal proximity.

Statistically, a hierarchical Bayesian regression examining efficiency scores revealed an interaction between progress condition and (linear) goal proximity (b = −0.07, CI [−0.12, −0.02], P < .0001; full coefficient estimates are provided in Table 1) as well as an interaction between progress condition and proximity^2 (b = 0.08, CI [0.03, 0.14], P < .0001), suggesting that participants exhibited a sharp uptick in efficiency (i.e., made more correct responses per second) near the end of a block, but only when they knew the block was nearly complete (Fig. 2).

Corroborating these patterns of efficiency scores, we separately examined RTs and accuracy separately in two mixed-effects regressions. Again, we found an interaction between progress condition and proximity^2 for both RT (b = 0.03, CI [−0.00, 0.06], P = .06) and accuracy (b = 1.02, CI [−0.04, 2.08], P = .03; see Table S2). Corroborating the observed time course of efficiency scores, these results suggest that, when progress information was available, responses speeded slightly near the end of a block and accuracy increased (Fig. S2). Conversely, when progress information was not available, participants' RTs progressively slowed and accuracy was stable over the course of a block, consistent with a general decrease in task engagement (Lorist et al., 2005). Taken together, these performance results are consistent with recent work showing that information about goal proximity engenders an increase in participants' effort investment (Devine et al., 2024)—specifically, participants responded more quickly and more accurately near the end of the block, but only when progress information was made available to them.

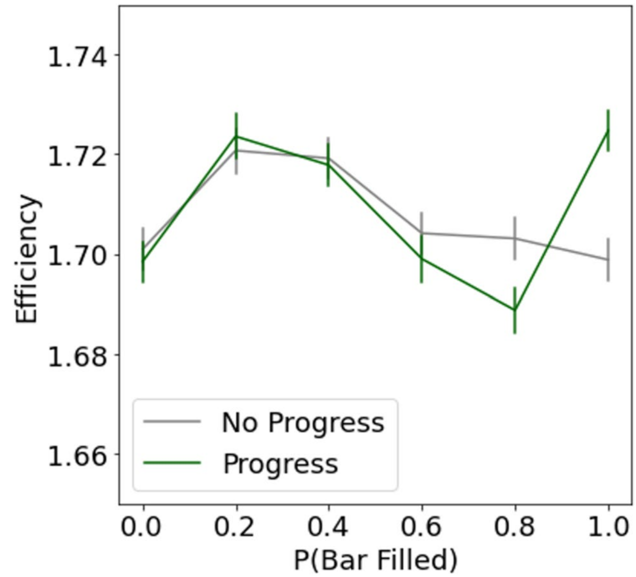

Fig. 2. Efficiency scores. The *x*-axis represents proximity to the end of a block, where larger values indicate nearer proximity. The *y*-axis represents participants' efficiency scores (accuracy/mean RT), where larger scores indicate faster processing (more accurate responses per second). Colour represents progress condition. Error bars reflects one standard error of the mean. (Colour figure online)

Table 1 Mixed-effect regressions results for efficiency scores during the oddball task

Coefficient	b	95% CI	P
Intercept	1.71	[1.68, 1.74]	.00
Prog. Cond.	0.01	[0.00, 0.02]	.01
Proximity	0.02	[−0.02, 0.07]	.14
Proximity^2	−0.03	[−0.07, 0.01]	.08
Block Num.	0.01	[0.01, 0.01]	.00
Prog. Cond. $\times$ Proximity	−0.07	[−0.12, −0.02]	.00
Prog Cond $\times$ Proximity^2	0.08	[0.03, 0.14]	.00

Gaze towards progress bar

Figure 3 depicts participants probability of gazing towards the progress bar, across block types, as a function of block (i.e., goal) progress. Unsurprisingly, across trials, participants were more likely to gaze towards the progress bar when it conveyed information about block progress (progress blocks: P(Gaze) = .36, no-progress blocks: P(Gaze) = .14; b = 2.42, CI [2.26, 2.58], P < .0001). Of particular interest in our study was the time course of participants' fixations to the progress bar in blocks where the progress bar conveyed information about goal progress. We observed that on progress blocks, participants' likelihood of gazing towards the progress bar rose sharply near the end of a block, suggesting that participants increased their monitoring of goal progress as they approached the goal state. Again, and unsurprisingly, when progress information was not available, participants' rate of progress monitoring remained steadily low throughout the block. This pattern was confirmed, statistically, by a positive interaction between progress condition and proximity^2 (b = 0.96, CI [0.06, 1.84], P = .02; see Table 2). The analysis of gaze behaviour suggests that as participants approached a goal, they became increasingly likely to direct attention to progress information, which lends support to the salience hypothesis, but does not support the uncertainty hypothesis.

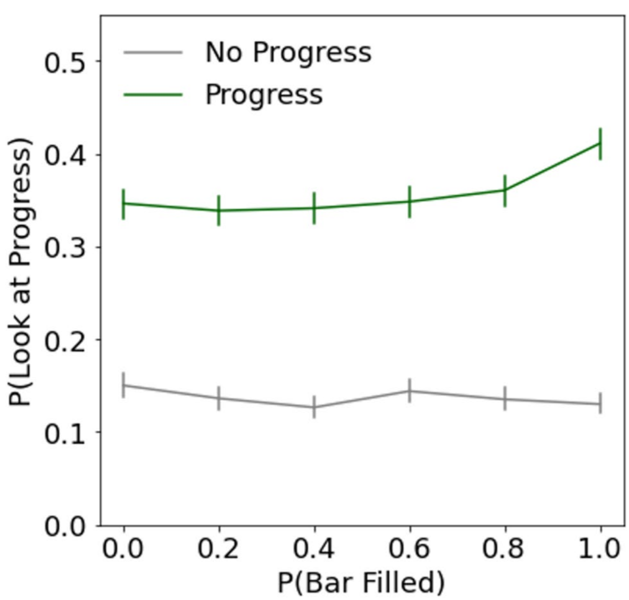

Fig. 3 Fixations towards the progress bar during the progress sampling phase. The *x*-axis represents proximity to the end of a block, where larger values indicate nearer proximity. The *y*-axis represents the proportion of trials where participants looked at the progress bar. Colour represents progress condition. Error bars reflects one standard error of the mean. (Colour figure online)

Table 2 Mixed-effect regressions results for progress monitoring (fixation) data

Coefficient	b	95% CI	P
Intercept	−2.01	[−2.56, −1.46]	.00
Prog. Cond.	2.42	[2.26, 2.58]	.00
Proximity	−0.84	[−1.33, −0.34]	.00
Proximity^2	1.10	[0.64, 1.56]	.00
Block Num.	−0.05	[−0.05, −0.04]	.00
Prog. Cond. $\times$ Proximity	−0.19	[−1.06, 0.7]	.33
Prog Cond $\times$ Proximity^2	0.96	[0.06, 1.84]	.02

Tonic pupil diameter

Finally, in an exploratory analysis, we examined tonic (i.e., slow-varying) pupil diameter over the course of a block as a function of goal proximity (Table 3). We did so because slow-varying, non-stimulus-evoked, tonic pupil diameter has been demonstrated to reflect changes in task engagement, attentional control, and planning (van den Brink et al., 2016; Unsworth & Robison, 2016; Unsworth et al., 2018).

First, we observed that tonic pupil diameter was smaller in progress blocks relative to no-progress blocks (b = −0.02, CI [−0.04, 0.00], P = .01; see Fig. 4). We reasoned, however, that this condition difference may simply reflect differences in stimulus luminance between conditions stemming from the progress bar display, and thus this was of little theoretical interest to us. More interestingly, while tonic pupil diameter in both progress conditions decreased over the course of a block (interaction between progress condition and [linear] proximity: b = −0.21, CI [−0.32, −0.10], P < .0001), we also observed a strong interaction between progress condition and proximity^2 (b = 0.22, CI [0.10, 0.33], P < .0001), indicating that tonic pupil diameter increased precipitously near the end of progress blocks when participants were near a goal (and presumably aware of their proximity to the goal). Notably, when information about participants' proximity to a goal was not available (during no-progress blocks), this pattern was substantially weaker. Importantly, this interaction describes changes in the slope of tonic pupil diameter

Table 3 Mixed-effect regressions results for tonic pupil data

Coefficient	b	95% CI	P
Intercept	0.02	[−0.02, 0.07]	.18
Prog. Cond.	−0.02	[−0.04, 0.00]	.01
Proximity	−0.38	[−0.44, −0.32]	.00
Proximity^2	0.31	[0.25, 0.36]	.00
Block Num.	−0.01	[−0.01, −0.01]	.00
Prog. Cond. $\times$ Proximity	−0.21	[−0.32, −0.10]	.00
Prog. Cond. $\times$ Proximity^2	0.22	[0.10, 0.33]	.00

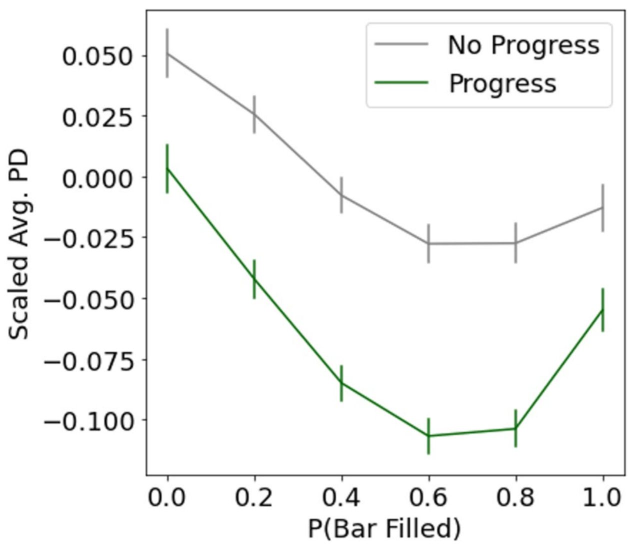

Fig. 4 Tonic pupil size over the course of a block. The *x*-axis represents proximity to the end of a block, where larger values indicate nearer proximity. The *y*-axis represents the (standardized) average pupil diameter. Colours represent progress conditions. Error bars represent one standard error of the mean. (Colour figure online)

within progress conditions over the course of a block (rather than between progress conditions), mitigating the possible contribution of between-condition luminance differences to the observed time-course difference

We also considered, in light of the observation that participants gazed more frequently at the progress bar near the end of a block in the progress condition (Fig. 3) that the observed interaction in tonic pupil size (i.e., the uptick near the end of a progress block) could be explained by more frequent gazes to the progress bar (whose luminance increased over the course of a block). We reasoned that this explanation is unlikely because an increased rate of fixations to the progress bar would result in an unequivocal decrease in in pupil diameter as the block progresses (Mathôt, 2018), but instead, we observed a marked *uptick* in tonic pupil size near the end of a block in the progress condition (Fig. 4). In other words, it is difficult to explain this observed interaction (uptick in tonic pupil size) purely with a luminance response. If anything, these differences in luminance may contribute to an underestimation of the magnitude of the end-of-block uptick in tonic pupil diameter observed here (Peysakhovich et al., 2017).

Discussion

Exerting sustained cognitive effort is taxing and aversive, and these effort costs accrue with continued exertion (Matthews et al., 2023; Wiehler et al., 2022). At the same time, both recent (Devine et al., 2024; Emanuel et al., 2022; Katzir et al., 2020) and classical (Brown, 1948; Epstein & Fenz, 1965; Hull, 1932) examinations of goal gradients finds that effort exertion should uptick near the end of a task—when a goal state is proximal. While recent work has renewed interest in the goal gradient hypothesis (Devine et al., 2024; Emanuel et al., 2022), little is known about the attentional dynamics governing *when* people seek information about goal proximity. Here, we examined individuals' progress monitoring behaviour over the course of a demanding attentional oddball paradigm, for which Devine et al. (2024) recently observed goal gradient effects in task performance.

Conceptually replicating previous results (Devine et al., 2024), we found that participants appeared to increase their effort as a function of goal proximity (i.e., block progress), making more correct responses per second near the end of a block (Fig. 2). More interestingly, we found that the rate at which participants attended to progress information—operationalized here as the frequency of gazes towards the progress bar—increased steeply near a goal state (Fig. 3). In other words, participants extracted information from the progress bar at a higher rate when goals were proximal (versus distal). This pattern of results could be interpreted in two ways.

On the one hand, this dual pattern of shifting attention to progress information and increased cognitive resources allocated to the task could be strategic—people may attempt to withhold cognitive resources early in a task and deploy them when they become aware that a task is nearing its end (Matthews et al., 2023; Vermeylen et al., 2024). This sort of "use it or lose it" strategy is analogous to pacing strategies observed among elite runners, wherein athletes store metabolic energy over the course of a race and deplete their reserves in a final leg of a race (Tucker et al., 2006).

On the other hand, increased attention to progress information near the end of a task may arise reflexively through a Pavlovian learning process. As a goal nears, people may orient their attention to features of a task that signal upcoming reward (Le Pelley et al., 2015)—here, the progress bar, which, when full, signals goal attainment (i.e., the end of the block). On this view, goal gradients resemble, qualitatively, sign-tracking behaviours, wherein attentional and cognitive resources are allocated towards a progress-communicating stimulus solely because it is associated with a goal or reward (Anselme & Robinson, 2020; Tomie et al., 1989). On the basis of the observed patterns of gaze behaviour, it is difficult to disambiguate these two accounts as both predict a qualitatively identical pattern of results—increased progress monitoring near the end of a task. Future work should aim to more specifically characterize these goal-gradient-like patterns in attention towards progress information.

The eye-tracking methodology used here also afforded an exploratory examination of how tonic pupil diameter varies as a function of goal proximity. Mirroring the observed time courses of performance and gaze behaviour in the progress condition, we observed that while tonic pupil diameter initially decreased over the course of a block, it increased precipitously as participants approached the end of a block (the goal state). While we had no strong predictions about tonic pupillary activity as a function of goal progress, it is worth noting that previous work has found that periods defined by larger tonic pupil diameter are associated with variability in the rate of evidence accumulation in perceptual decision (Murphy et al., 2014), while other studies have observed that optimal performance in attentionally demanding tasks occurs during periods defined by intermediate ranges pupil size (van den Brink et al., 2016; Murphy et al., 2011). As these putatively endogenous (nontask evoked) shifts in pupil diameter have been linked to changes in control state (Gilzenrat et al., 2010), it is interesting to note that the precipitous increase in tonic pupil diameter we observed near a goal state was accompanied by an increase in the rate of correct responses per second performance, which may signal a change in control state—possibly evoked by goal state proximity—characterized by greater attentional engagement.

With these results in mind, it is worth noting some limitations of the present work. By design, our task paradigm temporally separated the presentation of progress information—and thus, the measurement of progress-monitoring behaviour via gaze—from the presentation of the task stimuli. While this design feature departs from our previous study (Devine et al., 2024), in which the progress bar and the oddball stimuli were presented simultaneously, it may not fully capture the trade-off inherent to many real-life situations in which information sampling and task performance inherent trade-off (e.g., looking up at the clock during an exam). Future work should aim to examine progress-monitoring behaviour in more ecologically valid contexts that entail such a trade-off.

Nevertheless, taken together, the present results extend past work on goal gradients in human effort exertion. Specifically, extending our previous findings (Devine et al., 2024), we find that, much like cognitive performance, attention towards progress information increases in proximity to a goal. In short, people attend to progress information more as they approach a goal.

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Author contributions S.D. conceived of the initial research question, designed and programmed all experiments, collected and analysed data, and co-authored the manuscript. M.R. co-supervised the project and co-authored the manuscript. A.R.O. supervised the project, assisted in the conception and design of the experiments, secured funding, and co-authored the manuscript.

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Data availability All task code, materials, raw data, analysis scripts, results, and compiled models are openly available online (https://github.com/seandamiandevine/eyeprog).

Code availability All task code, materials, raw data, analysis scripts, results, and compiled models are openly available online (https://github.com/seandamiandevine/eyeprog).

Declarations

Competing interests The authors declare no conflict of interest.

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Consent to participate All participants provided written informed consent prior to participation.

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