Effects of feedback framing and regulatory focus are task-dependent

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INTRODUCTION

The Problem

Training paradigms often depend on performance feedback to enhance motivation, increase enagement, and improve performance. However, the effects of feedback on task performance are mixed (Hattie & Timperley, 2007; Kluger & DeNisi, 1996). These mixed results may be explained by how individuals differ in their reactions to specific types of feedback, but this variability is often difficult to predict. Furthermore, task properties may influence feedback effectiveness. Feedback intervention theory, (FIT; Alder, 2007; Kluger & DeNisi, 1996) states that feedback interventions regulate behavior by changing the focus of attention to a particular discrepancy between performance and standards. Individual differences in goal orientations (i.e., trait regulatory focus) influence attentional focus, as well as intrinsic goals or standards, and therefore likely impact whether and to what extent feedback influences future performance. More study is needed investigating the effectiveness of feedback within the context of individual differences and their interactions with tasks and domains to inform learner models and better implement individually optimized instructional strategies.

Relevance to GIFT

The design of GIFT incorporates users' individial traits to deliver tailored training. One of GIFT's major design principles includes the delivery of individually tailored instructional interventions using empirically based generic instructional strategies (Wang-Costello, Goldberg, Tarr, Contron, & Jiang, 2013). GIFT contains mechanisms to select appropriate feedback for given training tasks. Further refining a model which incorporates task properties and individual responses to feedback would improve GIFT's ability to provide more tailored and effective training. What we present is (1) a particular trait to consider and (2) the implications that task properties may have in determining effective feedback.

In the present work, we looked at the interaction of task affordances and trait regulatory focus as possible predictors of feedback effectiveness to inform GIFT's existing models. Results can be incorporated into learner models but may also require domain module information for proper implementation.

Regulatory Focus and Regulatory Fit

Regulatory focus is a goal orientation construct (Higgins, 1998; Higgins et al., 2001) that contains two distinct motivational orientations that describe an individual's propensity to approach gains or avoid losses: promotion focus and prevention focus. Highly promotion-focused individuals have a tendency to pay more attention to opportunities for gain and are motivated by intrinsic ideals as compared to highly prevention-focused persons whose motivations are rooted in extrinsic obligation and avoidance of loss (Higgins, 1998; Van-Dijk & Kluger, 2004). These propensities may have implications for responses to strategic affordances in tasks, such as eagerness/approach strategies and vigilance/avoidance strategies (Higgins et al., 2001). Promotion and prevention scores are largely independent of each other (Summerville & Roese, 2008), and can be obtained from questionnaires such as the Regulatory Focus Questionnaire (Higgins et al., 2001).

Regulatory fit theory (Higgins, 2000) predicts that when an individual's regulatory focus is matched with the nature of a goal, object, or reward structure framing (i.e. point-gains for promotion and point-losses for prevention), a more motivated and engaged state is elicited as compared to when they do not align. According to this theory, matching a highly promotion-focused individual with feedback framed in terms of gains should yield a more motivated and engaged learner as compared to a highly prevention-focused individual and vice versa. In addition, the nature of the task itself and its strategic affordances should also influence regulatory fit. To investigate whether regulatory fit theory may be useful to incorporate in learner models, we examined the effects of regulatory focus, feedback framing, and task affordances within the context of two inhibitory control go/no-go tasks that varied in the timing and number of trials.

Inhibitory Control

Inhibitory control involves the ability to override or halt an otherwise automated response, especially when that automated response is wrong or inappropriate. The ability to suppress inappropriate responses is essential for healthy living and functioning. Difficiences in inhibitory control contribute to the risk of engaging in maladaptive behaviors such as alchohol abuse (Kamarajan et al., 2004), poor sleep hygiene (Todd & Mullan, 2014), drug use (Fillmore & Rush, 2002), and over-eating (Houben, 2011). Individuals with a difficiency in inhibitory control experience difficulties with decision making (Shenoy & Yu, 2011), executive function and working memory (Carlson, Moses, & Claxton, 2004). Some work has shown that inihibtory control can be improved with training (Berkman, Kahn, & Merchant, 2014). For example, one week of inhibitory control training significantly reduced civilian casualties in a simulated hostage situation (Biggs, Cain, & Mitroff, 2015). Inhibitory control can be trained using a go/no-go task, in which participants are asked to press a button in response to a "go" stimulus and withhold a response to a "no-go" stimulus. The simplicity of go/no-go paradigms makes them an excellent testbed for examining the effects of individual traits, feedback framing, and task strategic affordances. The flexibility of go/no-go paradigms allows the same basic task to be performed using different strategic affordances, which may be encouraged via subtle changes of stimulus timing.

Current Research

We tested the effectiveness of regulatory fit as a means of increasing performance on an inhibitory control training task in two experiments using different trial timelines. Based on previous literature that supports regulatory fit's ability to elicit a more motivated state, we predicted in both cases that the training would be more effective when the feedback framing matched the trainee's regulatory focus and the task's strategic affordances. Both experiments showed effects of regulatory focus, but the effects were different in the two experiments. In Experiment 1, the more prevention-focused the individual, the better they learned under the loss-framed feedback condition. In Experiment 2, the more promotion-focused the individual, the worse they learned under a points-free feedback condition. The differences may have resulted from different task affordances in the two experiments: a vigilant strategy (loss-avoiding) in Experiment 1 vs. an eager strategy (gains-seeking) in Experiment 2. Overall, these results highlight the relevance of regulatory focus for learner models, the complexity of regulatory fit (i.e., 3-way rather than 2-way fit), and how influential a small change in a task can be, if it changes the task's strategic affordances.

METHODS

Two similar experiments were run, differing in their number of participants and the timing and number of trials in the training task. Experiment 1 included 103 participants. Data from 10 of those participants were excluded based on pre-specified performance criteria, leaving 93 participants. Experiment 2 included 33 participants, of which 3 were excluded based on the same criteria, leaving 30 participants. Experiment 2 had fewer participants, because it was designed as a small-scale pilot for a future planned experiment. The voluntary, fully informed written consent of participants in this research was obtained as required by Title 32, Part 219 of the CFR and Army Regulation 70-25. All human subjects testing was approved by the Institutional Review Board of the United States Army Research Laboratory.

After completing an online pre-screener, participants were tested for normal visual acuity and color vision and completed a battery of questionnaires including the RFQ. After completing the questionnaires, participants completed the training task. In both experiments, the training task was a speeded go/no-go task with a computer-rendered character holding a gun as the go stimulus and the same character wearing different clothes and not holding a gun as the no-go stimulus. Go stimuli were four times as frequent as no-go stimuli. In both experiments, stimuli were visible for 400 ms and were presented at a randomized location on the screen. Participants had a limited time to press a response button in response to a go stimulus. In Experiment 1, participants were required to respond within 500 ms of image onset, whereas in Experiment 2, participants were required to respond within 1 s. After this deadline, feedback (see below) was displayed for 500 ms. In Experiment 1, the next trial began 500 ms after the end of the feedback, but in Experiment 2 the next trial began between 1 and 2 seconds later (uniform distribution).

Training in Experiment 1 consisted of 30 blocks of 30 trials each, lasting 20-30 minutes total. In Experiment 2, training consisted of 20 blocks of 30 trials each; because the trials were longer, training lasted 20-30 minutes.

After the training task, participants completed questionnaires about the training task. Next, participants completed the transfer task. The transfer task was a desktop simulation of being a passenger/spotter in a vehicle patrol of a middle-eastern-themed town with intermittent fog. As the vehicle proceeded, images would pop into the environment. The task was to classify those images as threats or non-threats, and to press a corresponding response button within 1 s of image onset. Two of the images were the go and no-go images from the training task. The other two were a table either with (threat) or without (non-threat) a table cloth obscuring the view under the table. In total, there were 200 images. Periodically, a diffuse fog would obscure the view to make the task more difficult. There were 5 periods of fog and 5 periods of no-fog, each averaging 1-minute in duration, and the transfer task took 10 minutes total. Finally, the participants completed another set of questionnaires.

The main independent variable of both studies was the framing of feedback in the training task. Participants were randomly assigned to point-gain-based feedback, point-loss-based feedback, or an informative control. In both the point gain and loss conditions, go trials were worth 30-60 points, with faster responses receiving more points and no-go trials were worth 180 points. In the gain condition, participants began with no points, and points were presented as gains. In the loss condition, participants began with the maximum points possible for a block, and points were presented as losses. For example, an average response time on a go trial in the gain condition would earn +45 points, but in the loss condition it would lose 15 points. These scoring systems are mathematically identical, but differ only in their framing. The control feedback showed a green check or red x to indicate correctness, and in the case of a response on a go trial, it also indicated response time.

Many outcome variables were measured; here we focus on two of them to illustrate the different outcomes of the two experiments. These outcomes are change in correct rejection (i.e. successfully not responding on no-go trials) rate over the course of training (i.e. the first 3 blocks vs the last 3 blocks), and accuracy in responding to the character stimuli out of fog in the transfer task. Both of these quantities are typically expressed as proportions, but for analysis they were analyzed as the logarithm of odds ratios (i.e. logit-transformed) in order to better meet the assumptions of linear modelling. Data from both experiments were combined and analyzed using a linear model with predictors of prevention strength, promotion strength, feedback condition (dummy coded), and experiment (1 or 2). The model included interaction terms for each strength with condition and experiment, condition with experiment, and the three-way interactions of strength, condition and experiment. Coefficients are reported with uncorrected 95% confidence intervals, and p-values are reported both uncorrected and corrected for multiple comparisons using false discovery rate (FDR).

RESULTS

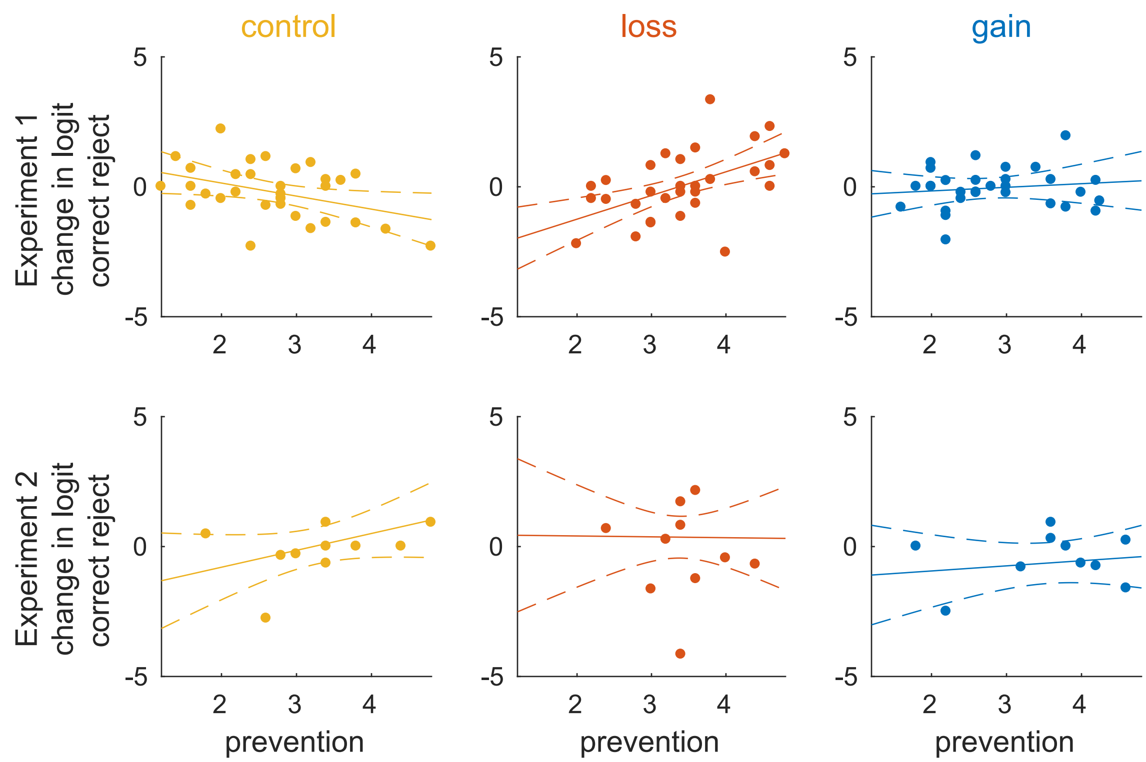

Figure 1. Change in logit correct rejection rate in control, loss and gain conditions across Experiments 1 & 2. Circles show individual participant results. Solid lines show expected values, and dashed lines show 95% confidence regions of the expected values.

Regression coefficient estimates with 95% confidence intervals appear in Table 1. There were no statistically significant effects of promotion strength on change in the logit correct rejection rate; however, there were effects and interactions involving prevention score, loss framing, and the experiment (1 or 2). The experiment term interacted with the effect of prevention strength, $B = 1.15$ [0.21, 2.10] $T(105) = 2.42$, $p = .017$ ($p = .065$ FDR), the loss condition $B = 10.86$ [1.7, 20.02] $T(105) = 2.35$, $p = .021$ ($p = .070$ FDR), and their interaction, B=-2.10 [-3.78, -0.41], $T(105)$=-2.47, $p = .015$ ($p = .064$ FDR). These interactions are visualized with slice plots (Figure 1) showing how expected change in the logit correct rejection rate varies with prevention strength under the three conditions and in the two experiments when promotion strength is held constant at the sample average.

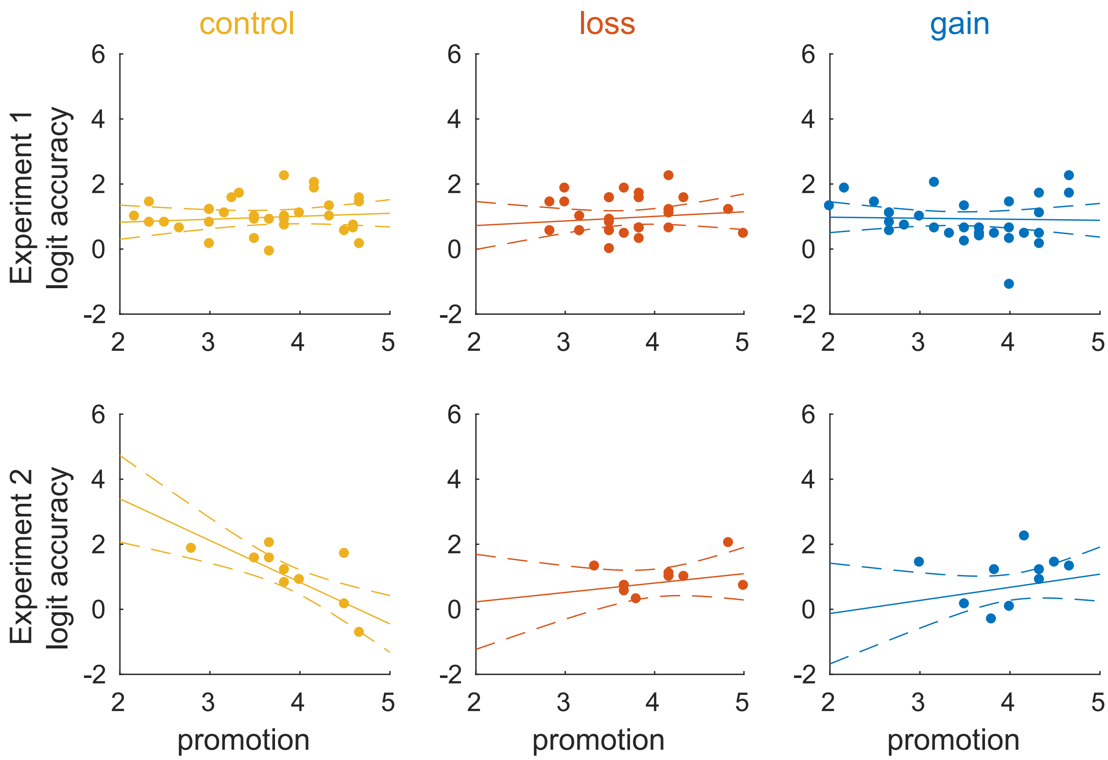

Figure 2. Logit accuracy on the trained stimulus with no fog in control, loss and gain conditions across Experiments 1 & 2. Circles show individual participant results. Solid lines show expected values, and dashed lines show 95% confidence regions of the expected values.

In the analysis of logit accuracy on the transfer task (Figure 2), the experiment factor interacted with promotion strength, $B = -1.37$ [-2.12, -0.63], $T(105) = -3.66$, $p < .001$ ($p = .007$ FDR), the interactions of promotion strength with loss framing, $B = 1.52$ [0.43, 2.62], $T(105) = 2.76$, $p = .007$ ($p = .043$ FDR), and promotion strength with gain framing, $B = 1.81$ [0.72, 2.90], $T(105) = 3.28$, $p = .001$ ($p = .014$ FDR). These reflect a negative effect of promotion strength on performance in the control condition in Experiment 2 that was not apparent in Experiment 1; moreover, this negative effect is counter-acted in both the gain and the loss conditions by effects in the opposite direction of the coefficient on the control condition.

Table 1. Regression coefficients and statistics

	B	95% CI		tStat	p	FDR
Change in logit correct rejection rate						
(Intercept)	1.57					
prev.	-0.50	-0.96	-0.04	-2.16	.033	.091
pro.	-0.11	-0.63	0.41	-0.43	.669	.711
loss	-6.72	-10.84	-2.60	-3.23	.002	.014
gain	-2.63	-6.08	0.82	-1.51	.134	.239
Exp. 2	1.09	-4.36	6.54	0.40	.692	.713
prev:loss	1.41	0.72	2.10	4.06	.000	.003
pro.:loss	0.68	-0.23	1.59	1.47	.143	.244
prev.:gain	0.64	-0.05	1.34	1.83	.070	.158

Continues

Table 1 Continued						
	B	95% CI		tStat	p	FDR
Change in logit correct rejection rate						
pro.:gain	0.28	-0.48	1.04	0.74	.464	.563
prev:Exp. 2	1.15	0.21	2.10	2.42	.017	.065
pro.:Exp. 2	-1.17	-2.56	0.21	-1.68	.096	.188
loss:Exp. 2	10.86	1.70	20.02	2.35	.021	.070
gain:Exp. 2	-3.05	-11.78	5.67	-0.69	.489	.574
prev.:loss:Exp. 2	-2.10	-3.78	-0.41	-2.47	.015	.064
pro.:loss:Exp. 2	-1.10	-3.14	0.93	-1.07	.286	.405
prev.:gain:Exp. 2	-1.09	-2.40	0.21	-1.66	.100	.188
pro.:gain:Exp. 2	1.46	-0.57	3.49	1.42	.157	.255
Logit accuracy for trained stimuli out of fog						
(Intercept)	1.04					
prev.	-0.13	-0.38	0.12	-1.03	.304	.414
pro.	0.09	-0.19	0.37	0.65	.518	.587
loss	-1.48	-3.70	0.74	-1.32	.189	.279
gain	-0.81	-2.66	1.05	-0.86	.391	.492
Exp. 2	3.16	0.23	6.10	2.14	.035	.091
prev:loss	0.41	0.04	0.78	2.21	.029	.090
pro.:loss	0.05	-0.44	0.54	0.20	.843	.843
prev.:gain	0.39	0.02	0.76	2.07	.041	.099
pro.:gain	-0.12	-0.53	0.29	-0.60	.552	.606
prev:Exp. 2	0.70	0.19	1.21	2.73	.008	.043
pro.:Exp. 2	-1.37	-2.12	-0.63	-3.66	.000	.007
loss:Exp. 2	-4.15	-9.08	0.77	-1.67	.097	.188
gain:Exp. 2	-6.20	-10.89	-1.51	-2.62	.010	.049
prev.:loss:Exp. 2	-0.63	-1.54	0.27	-1.39	.169	.261
pro.:loss:Exp. 2	1.52	0.43	2.62	2.76	.007	.043
prev.:gain:Exp. 2	-0.36	-1.06	0.35	-1.01	.317	.414
pro.:gain:Exp. 2	1.81	0.72	2.90	3.28	.001	.014

DISCUSSION

Although both experiments demonstrated effects of regulatory fit between participant regulatory focus and feedback framing, the effects were different. This suggests that regulatory focus could usefully be incorporated into individual learner models, but that these models might also need to be task-dependent. The differences between our two experimental training tasks were in the timing and number of the trials. The different regulatory fit relationships may result from the different strategic affordances these timing differences offer. In Experiment 1, responses were required to be fast (< 500 ms), and there was no variability in the inter-trial-interval. These factors together may have encouraged a strategy in which responding was essentially automatic unless it was canceled by some inhibitory process. In other words, success on this version of the task may have relied upon the participant adopting a vigilant strategy of avoiding false alarms on no-go trials. In Experiment 2, the slower pace and the unpredictability of stimulus onset might have reduced the automaticity of the go response, so rather than focusing on avoiding errors, participants might have focused on quickly reacting to stimuli and therefore relied on an eager/approach strategy. With only

30 participants, this interpretation should be considered tentative until more data is collected. Taken together, these experiments are consistent with the effect of feedback framing on performance depending on a three-way interaction among individual regulatory focus, feedback framing, and the strategic affordance of the task in question.

The three-way interaction has practical consequences, in that it would lead to recommending different point-based feedback interventions based not only on an individual's regulatory focus but also on the nuances of the task. For example, framing feedback in terms of loss of points appears beneficial for training prevention-focused individuals, but only if the task itself has a prevention-like (e.g., vigilant) strategy. Applying loss-based feedback for prevention-focused individuals in other tasks may not be helpful. In the case of Experiment 2 (eager/approach task strategy), we found that the more promotion-focused an individual, the worse they did in the absence of point-based feedback. Either gain-framed or loss-framed points feedback eliminated this performance decrement. This unexpected result may have come about due to the extra and more variable timing in the second experiment. There may have been just enough time to allow the promotion-oriented participants to interpret either form of point-based feedback as indicative of achievement. This highlights the potential complexity of regulatory fit theory and of its application in practice.

Overall, our findings point toward the need to include regulatory focus as a trait in individual learner models (see also Reinerman-Jones, Lameier, Biddle, & Boyce, 2017), as a potential source of adaptation (Goldberg et al., 2012) in training frameworks. More work is needed to develop an ontology of tasks and their strategic affordances in order to better predict the interaction effects of regulatory focus with different kinds of feedback, and the resulting effects on learner performance. Stronger predictive models could be incorporated into GIFT to support optimal feedback framing selection in different task domains.

CONCLUSIONS AND RECOMMENDATIONS FOR FUTURE RESEARCH

This work examined the effects of regulatory focus and feedback framing on performance in two go/no-go training tasks that differed in the timing and number of trials. Three major conclusions stem from this work.

1) Regulatory focus is an important individual trait worth including in learner models for improving training outcomes.

Regulatory focus describes an individual's goal orientation. It is an individual trait tied to reward-based behavioral motivation, and thus is expected to influence how different individuals respond to reward-based training interventions and feedback. Our work revealed significant effects of regulatory focus on how individual trainees responded to feedback framing in a go/no-go paradigm. Trainees' prevention focus or promotion focus, under different feedback conditions and different strategic affordances, predicted performance improvements or decrements. Regulatory focus is simple to measure with a short questionnaire and can be included in learner models. These may be used by learner modules to determine states and thus help pedagogical agents select appropriate feedback framing options to maximize performance.

2) Regarding regulatory fit theory, a 3-way model of regulatory focus x feedback-framing x task strategic affordances may be more predictive of training outcomes than the traditional 2-way model of regulatory focus x feedback-framing.

The timing differences in our go/no-go paradigms yielded outwardly similar tasks that nonetheless differed in their strategic affordances. The first experiment's task encouraged a vigilant (i.e., error-avoiding) strategy by creating a rhythmic, pre-potent response to go stimuli that required inhibitory control to prevent that response in no-go trials. The second experiment's task encouraged a more eager (i.e., achievement-seeking) strategy by rewarding rapid response to go stimuli that were less predictable in their onset. By exploring the relationship between regulatory focus and feedback framing on two strategically different tasks, we uncovered evidence of a 3-way regulatory fit effect. The mechanisms underlying this effect remain to be examined in future work. Measurements of motivation, attention, or other affective or physiological states may shed light on what mediates the 3-way regulatory fit effect.

3) Small differences in training tasks, such as the timing differences in our study, may substantially affect the way that human variability dimensions interact with feedback framing and other personalized training interventions.

The scientific literature shows mixed results for a variety of training interventions, including various points-based reward schemes used for gamifying training tasks (Hamari, Koivisto, & Sarsa, 2014; Hanus & Fox, 2015; Seaborn & Fels, 2015) One possible explanation for this variability is that superficially similar tasks may in fact encourage different strategies, and the most effective feedback framing may depend on the strategy that the task is encouraging trainees to use. In our study, a subtle difference in timing was enough to yield tasks that relied more or less on vigilant vs. eager strategies, even though both were go/no-go tasks with the same visual stimuli and same points-based feedback. This highlights a need to think clearly about what strategies a given training task may afford. It may be beneficial to develop an ontology of strategic affordances of candidate tasks and consult this when designing training interventions that rely on regulatory fit or, by extension, fit with other individual trainee traits or states. Strategic affordance may be a useful variable to include in domain modules in intelligent tutoring systems like GIFT.

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