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Emotion and information search in tactical decision-making: Moderator effects of feedback

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Abstract Information search during decision-making may be influenced both by selective attention and by the criterion used for ceasing to search. When the items searched are themselves emotive, the affective state of the decision-maker may bias these search processes. If an automatic selective attention bias operates, it may produce mood-congruent effects irrespective of context; e.g., negative affect may focus attention on negative items of information. An alternative possibility, suggested by the mood-as-input model, is that the influence of affect on search may depend on how decision-makers understand their emotions within a given context. The present study tested predictions derived from relevant theories of affective bias, using feedback as a means to generate a context of success or failure. Hundred and sixty participants were required to access positive and negative items of information in choosing between different routes for a search-and-rescue mission. Outcomes of choices were manipulated experimentally, so that in one condition participants received mostly positive feedback, and in a second condition participants received mostly negative feedback. Results showed that the feedback manipulation influenced affect, but there was considerable variation in affective state within each condition. Associations between affect and information search were moderated by feedback condition. For example, positive affect was associated with more frequent sampling of positive information in the negative feedback condition, but the association reversed when feedback was positive. Findings were consistent with the mood-as-input hypothesis, but not with an automatic selective attention bias. Context may influence how the decision-maker interprets their affective state.

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Introduction

Affect (emotion and mood) has often been identified as a key factor in decision-making (Loewenstein et al. 2001). Information search is one of various critical processes for real-world tactical decision-making (Dhami and Harries 2010). Often, there is more potentially relevant information available than can easily be assimilated by the decision-maker. In applied settings, neglect of potentially important data may be exacerbated by new technology that delivers high volumes of information. The search for information may be influenced by both the emotional state of the decision-maker, and by the emotional content of items of information. Imagine a doctor searching the internet for information on treatments for a rare disease. Different websites may provide both positive information (e.g., case studies of successful treatments) and negative information (e.g., side effects of drugs). How would the person's emotions influence search? The mood-congruence principle (Bower 1981) suggests that positive affect might focus search on websites likely to provide positive items of information, with negative affect biasing search towards negative items. However, little research has addressed emotional biases in information search in complex visual environments.

The remainder of this introduction is structured as follows. We identify selective attention and choice of stopping criterion as key processes for search. We outline theories of emotion and cognition that suggest how emotional states may impact these key processes. We describe an experimental paradigm for investigating affective bias in information search, and derive specific predictions from two relevant theories. The theory of selective attention bias (Mathews and MacLeod 2005) specifies an automatic, preattentive bias that may produce mood-congruent effects in search. The mood-as-input theory (Martin 2001) describes context-sensitive biases that are dependent on how decision-makers interpret their affective states.

Theories of information-search and affect

The mood-congruence principle is too broad to provide a detailed basis for prediction of the influence of affect on decision-making. A variety of contextual factors moderate the mood-congruence effect, so that a more detailed analysis of information-processing strategies is required (Bower and Forgas 2001). Furthermore, little research has been done on the influence of positive and negative affect on information search and it is unclear whether affective states produce a mood-congruent bias in search. Existing studies of mood and search either do not distinguish positive and negative items of information explicitly (Forgas 1991), or they focus on post-decisional processing, such as tendencies towards confirmation bias (Fischer et al. 2011).

What processes supporting information search might be sensitive to affect? Research on information search has typically focused on decision tasks that provide the person with multiple cues relevant to a binary choice (e.g., the cost, likely success, possible side-effects and other attributes of two alternate medical treatment options). Search is controlled by heuristic processes that simplify the cognitive demands on the decision-maker (Dhami and Harries 2010; Gigerenzer et al. 1999). Studies of internet search show that attention may initially be captured by salient or meaningful stimuli (Simola et al. 2011). Heuristics for search may also include both a rule for ordering search in terms of cue importance or priority, and a stopping rule that specifies when sufficient cues have been sampled to make the decision (Browne and Pitts 2004). Potentially, emotion could influence both initial attention to cues, and the stopping rule. Next, we discuss two leading theories of affective bias that are relevant to one or other of these processes. First, selective attention bias (Mathews and MacLeod 2005) might lead to attentional prioritization of cues congruent with the current emotional state. Second, the mood-as-input theory (Martin 2001; Marszał-Wiśniewska and Zajusz 2010) suggests that emotions may be used as a guide for whether or not to continue the search, depending on how those emotions are understood within the context provided by the task.

Selective attention bias is best known from studies of anxiety which use experimental paradigms such as the emotional Stroop and dot-probe tasks (Mathews and MacLeod 2005). Studies show that anxiety influences selective attention through enhanced processing of threat stimuli in anxious participants (Bar-Haim et al. 2007; Mathews and MacLeod 2005). Generalization of such effects to other emotions has been controversial; for example, bias in depressed patients may be restricted to a relatively slow, and post-attentional, elaborative process (Mogg and Bradley 2005). However, there is increasing evidence for depression biasing attention towards stimuli associated with sadness (Gotlib et al. 2004; Joormann and Gotlib 2007; Leung et al. 2009), and, similarly, anger biases attention to hostile stimuli or cues (Wilkowski et al. 2007). Attentional bias associated with positive moods has been considerably less studied than negative affective bias, but induced positive mood has been shown to slow response to positive words in the emotional Stroop test (Gilboa-Schechtman et al. 2000).

There is extensive research on the information-processing mechanisms for selective attentional bias (e.g., Mathews 2004). There may be multiple mechanisms involved, including both early, preattentive processes and voluntary attention (Bar-Haim et al. 2007; Matthews and Wells 2000). The role of automatic bias in preattentive processing is supported by evidence for operation of bias even when stimuli are masked and inaccessible to conscious awareness (Bar-Haim et al. 2007). However, the nature of bias may vary across stages of processing, and may differ across different emotions (Ellenbogen and Schwartzman 2009). Cognitive neuroscience models (Posner and Petersen 1990) suggest that attention is controlled by multiple neural networks, including one for spatial orienting. This theory also specifies the specific mechanisms that support spatial orienting: *disengaging* from the location attended initially, *moving* to a new spatial location, and then *engaging* the new location. Data from cueing studies (Derryberry and Reed 1997, 2002) links anxiety specifically to slower disengagement from threat; anxious persons tend to 'lock onto' potential sources of threat (Fox et al. 2002). Slow disengagement of attention from threat has also been attributed to impairment in top-down executive control, which may fail to inhibit orienting towards task-irrelevant threat stimuli (Eysenck and Derakshan 2011).

In naturalistic data-rich environments, such as information search on the internet, selective attention is critical for the decision-maker. Specifically, the bias hypothesis (Mathews and MacLeod 2005) suggests that the anxious decision-maker may find it difficult to disengage attention from threatening items of information (Fox et al. 2002), leading to a bias towards sampling threatening information. For example, in choosing between medical treatments for an illness, the person might become fixated on reports of side-effects of a drug, neglecting items of evidence for its effectiveness. Other mechanisms for attentional bias may also play a role in information search. Recent studies (Derakshan and Koster 2010; Matsumoto 2010) suggest that, in some circumstances, anxiety may influence initial attentional engagement with threat stimuli. Anxiety has also been linked to biases towards interpretation of ambiguous material as threatening (Bar-Haim et al. 2007), and towards framing decisions in terms of threat (Nabi 2003), processes that may also prioritize sampling of threat cues, or lower the priority of non-threatening information.

If selective attention bias is automatic (Bar-Haim et al. 2007), it should generate context-invariant biases in information search. For example, a negative-valent stimulus should always hold the attention of the unhappy decision-maker, irrespective of other circumstances. This prediction conflicts with accumulating evidence from a variety of empirical paradigms that show relationships between affect and information-processing are not fixed, but depend on how the affective state is interpreted in relation to specific self-regulatory challenges (Bless and Fiedler 2006; Das and Fennis 2008). That is, the context for information-processing may moderate the impact of affect. For example, Fishbach et al. (2010) describe a number of instances in which the effects of emotion-inducing feedback on motivation varied according to contextual factors such as the goal pursed by the individual, and beliefs about the meaning of feedback. Various theories of emotion are capable of accommodating contextual moderators (e.g., Clore and Huntsinger 2009). A theory of this kind that is particularly relevant to information search is the mood-as-input model (Martin 2001; Marszał-Wiśniewska and Zajusz 2010). It is based on the 'mood-as-information' hypothesis that moods and emotions provide cues that influence how one feels about objects and events (Schwarz and Clore 1983; Storbeck and Clore 2007). The mood-as-input hypothesis follows this principle, but assumes that moods have no inherent consequences for evaluative information-processing. Instead, moods act as inputs to evaluations, such as choices of processing style and self-regulative processes that are entirely dependent on the meaning of the mood within a specific context. The mood-as-input model has been used to explain how moods impact decisions to continue or stop work on a problem (Martin et al. 1993). Thus, it is relevant to information search which is similarly influenced by criteria for stopping search (Browne and Pitts 2004).

Studies based on the mood-as-input hypothesis highlight the varying motivational implications of affective states. For example, the effects of positive and negative moods on the decision to continue or stop processing differ sharply according to whether the instruction for the task is to continue the task until "you no longer enjoy it" or "you have done enough". A negative mood signals the person to stop in the former case, but continue in the second (Martin et al. 1993). Martin et al. (1993) delineate other instances in which positive versus negative mood differences may be reversed according to contextual factors. Recent work has also shown that affective context may moderate perseverative worry and rumination (Hawksley and Davey 2010), negotiating stance in bargaining (Carnevale 2008), and creativity (Davis 2009).

A decision-making scenario for investigating affect and information search

Matthews et al. (2011) developed a 'search-and-rescue' task for investigating the influence of emotion on information search within a relatively complex tactical decision-making environment. The participant chose the fastest route to reach a lost party of explorers based on information related to possible costs (i.e., threats) and benefits (gains in time) on each route. The participant actively searched for this information by using the mouse to sample cost and benefit icons pertaining to each route. Thus, decision was preceded by a potentially extended period of search across multiple information sources. Bias in search was indexed by the relative frequencies of sampling the cost and benefit icons.

The study tested the mood-congruence hypothesis derived from selective attention bias theory (Mathews and MacLeod 2005) that anxiety should be associated with increased sampling of threat-related information (i.e., potential risks). Anxiety was manipulated using music and guided imagery (Mayer et al. 1995), so that participants performed the task with either an anxiety or neutral mood induction. Measures of trait and state anxiety were also secured, and the mood induction was successful in raising state anxiety. Trait anxiety was associated with an attentional bias, such that anxious individuals accessed the cost icon more frequently than those low in trait anxiety. However, this effect was found only following a neutral mood induction. It was expected that the anxious mood induction, using music and guided imagery (Mayer et al. 1995), would enhance attentional bias related to anxiety. In fact, the anxiety effect found in the neutral condition disappeared, and anxiety was unrelated to information search. Thus, selective attention bias varied with the emotional context, a finding incompatible with an automatic mechanism for bias in anxiety which should divert attention to threat irrespective of context.

The mood-as-input hypothesis may help explain why the anxious mood induction eliminated effects of trait anxiety on information search in the Matthews et al. (2011) study. The mood induction may have provided a context that changed the significance of feeling anxious. Matthews et al. (2011) suggested that the mood-induction changed the frame for decision-making. In the neutral condition, consistent with prior evidence on anxiety and framing (Nabi 2003), anxious subjects may have framed decisions as requiring vigilance to threat within an otherwise safe environment, requiring elevated attention and analysis of threat, leading to more frequent sampling of the cost icon. Induced anxiety may generate a context of overt danger, reducing the motivation to actively search for threat. The frame for all participants may then have been one of escape from immediate danger, so that neither high- or low-anxiety persons were motivated to perform extensive search for threat.

Aims and hypotheses

The present study aimed to test whether affect influences search for information in a complex decision-making environment. A modified version of Matthews et al.'s (2011) search-and-rescue task was used, requiring the decision-maker to search for positive and negative items of information, using icons for potential costs and benefits on the map display. By contrast with the earlier study (Matthews et al. 2011) we aimed to focus on the general emotional states of positive and negative affect (PA and NA), and personality traits linked to affectivity, as well as more specific negative emotions. In addition, the study aimed to use a mood manipulation that derived directly from the participant's experience of the task, as opposed to the Mayer et al. (1995) induction used previously. Participants' attributions of the source of their emotions during performance can moderate the impact of mood inductions (Fishbach et al. 2010), and there may be some variability in attributions when an external induction is used. The present study used a success-failure manipulation to induce contrasting affective states. The effectiveness of both positive and negative feedback manipulations in changing affect was demonstrated in a meta-analysis of 32 experimental studies (Nummenmaa and Niemi 2004). Use of feedback provides an affective manipulation that may come closer to emotions experienced in real decision-making, where the outcomes of the decision-maker's choices are likely to be a major influence on affect. Fishbach et al. (2010) argue that affective response is the underlying mechanism through which feedback influences behavior.

Differing predictions may be derived from the theories outlined previously. Given that selective attention bias generalizes across a range of emotions (Gilboa-Schechtman et al. 2000; Leung et al. 2009), NA should be associated with bias towards searching for potential costs, whereas PA should relate to a preference for accessing potential benefits. We tested this hypothesis by examining correlations between the two dimensions of affective state and frequencies of sampling the two types of icon. The attentional bias theory (Bar-Haim et al. 2007) then predicts that high PA should be associated with frequency of sampling benefit icons and NA should be associated with sampling frequency for cost icons. If the bias reflects an automatic processing mechanism, the associations should thus be similar in both feedback conditions (assuming variation in affective state within each condition). In addition, the feedback manipulations should produce overall mood-congruent biases due to their effects on mood, e.g., greater sampling of cost icons in the negative feedback condition.

As previously suggested, the affective state of the decision-maker may influence the 'stopping rule' (Browne and Pitts 2004) used to terminate information search, consistent with the mood-as-input hypothesis (Marszał-Wiśniewska and Zajusz 2010). In relation to the search-and-rescue task, the importance attached to exhaustive search of potential benefits and costs may differ according to the success/failure context. It is intrinsically challenging to derive predictions from the mood-as-input hypothesis, because the critical factor driving cognitive bias is the meaning of the mood state for the person within a given context, and such meanings may reflect a variety of factors. However, tentative predictions may be derived as follows.

According to mood-as-input theory (Martin 2001, p. 138), individuals ask "What does it mean that I am feeling this way in this context?" Positive moods are compatible with success, and negative moods with failure. The meaning taken from the positive mood may then be that success is easily accomplished. A related idea is Carver and Scheier's (2000) hypothesis that positive affect may relate to coasting (i.e., easing off in pursuit of a rewarding goal). If success is a "given", then a cursory examination of the benefits offered by the different routes may suffice, so that positive mood may even discourage frequent sampling of possible benefits. Conversely, negative mood during failure signals that performance is likely to be impaired irrespective of what the decision-maker chooses, and there is little motivation to dwell on the costs of routes. By contrast, experiencing a negative mood in a success context may be interpreted as a sign that all is not as well as it seems, or that there may be some hidden danger or pitfall. In this case, negative mood may encourage vigilance and prolonging the search for possible threats. Similarly, experiencing positive mood in the course of failing at some task might suggest that some hope remains, motivating search for possible benefits that would provide an "escape route". Table 1 expresses how each type of mood may be experienced within failure and success contexts, and the possible implications for

Table 1 Possible interpretations of positive and negative moods experienced in the contexts of success and failure

	Success	Failure
Positive affect	*Easy accomplishment* Mood signals that success is easy; reduced motivation to search benefits	*Courage in adversity* Mood signals that despite failure, hope remains: increased motivation to search benefits
Negative affect	*Hidden dangers* Mood signals that despite success, dangers remain: increased motivation to search costs	*Resignation to failure* Mood signals that failure is likely; reduced motivation to search costs

motivations to curtail or prolong search for costs or benefits. On this basis, the mood-as-input hypothesis predicts that so that positive affect is positively associated with sampling possible benefits only in the failure condition, whereas negative affect is positively associated with sampling possible costs only in the success condition.

The study also aimed to investigate two subsidiary issues. We tested whether different aspects of negative affect were differentially related to information search. The specific emotions of anxiety, anger and depression were assessed. It was hypothesized that anxiety might relate more strongly to active search for costs than depression or anger, given that hypervigilance for threat may be central to anxiety (Eysenck 1992). A second subsidiary aim was to investigate the role of stable trait factors linked to emotionality. Extraversion (E) and neuroticism (N) are sometimes seen as equivalent to positive and negative affectivity, respectively (Lucas and Diener 2000). That is, E reliably correlates with PA, and N with NA, in a range of laboratory and field studies. Furthermore, extraverts tend to show a stronger PA response to rewarding stimuli, whereas high N individuals show an amplified NA response to threat stimuli. These findings have been attributed to the biological foundations of E and N in relation to brain reward and punishment systems, respectively (Corr 2009). On this basis, E was expected to relate positively to PA response to positive feedback, and N to NA response to negative feedback. Moreover, it is suggested that E relates to a bias towards processing stimuli of positive valence, whereas N (like trait anxiety) relates to a negative processing valence (Zelenski and Larsen 1999). In this case, E and N would be expected to relate to more exhaustive search of benefit and cost icons, respectively.

Method

Participants

Participants were 160 undergraduate psychology students from the University of Cincinnati (69 male; 91 female). Ages ranged from 18 to 34 years ($M = 19.95$, SD $= 2.49$). Participants received course credit for participation.

Questionnaire measures

The revised Eysenck Personality Questionnare (EPQ-R: Eysenck et al. 1985) was used to assess the E and N traits. Affective states were assessed with two instruments. The PANAS (Watson et al. 1988) measures positive affect (PA) and negative affect (NA). Instructions asked respondents to report their current mood state. The State-Trait Personality Inventory (STPI: Spielberger and Reheiser 2004) was used here to measure state and trait anxiety, anger and depression. The National Aeronautics and Space Administration Task Load Index (NASA-TLX: Hart and Staveland 1988) was used to assess the workload of the decision-making task. The participant rated six components of mental workload, following performance: mental demands, physical demands, temporal demands, performance, effort, and frustration. Each component was rated on a single 0–10 scale.

Decision-making task

The task required the participant to rescue a 'lost party' in the Antarctic by choosing the best route for driving a snowcat vehicle to their location. The task was made up of a series of discrete items (a sample display is shown in Fig. 1). Each item presented the participant with a map of

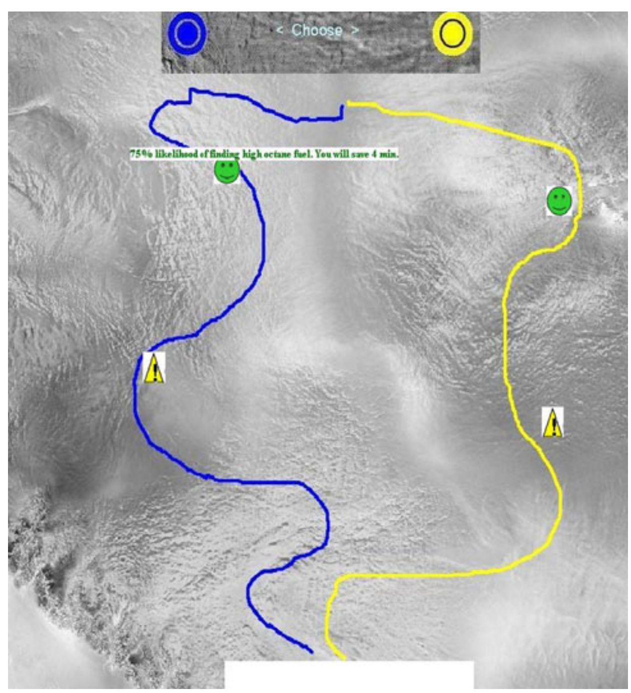

Fig. 1 Sample display of one trial item, showing the *green*, "smiley face" benefit icons and the *yellow* "caution" cost icons for each route (Color figure online)

the terrain with symbols indicating the positions of the participant and the lost party. Two alternative, color-coded routes were shown. The participant had a target time of 90 min to complete that stage of the journey, but each route carried potential costs (risks) and potential benefits that might influence journey time. Participants could examine the potential time costs and benefits of each route, by using the mouse to place a cursor over icons representing costs and benefits. Accessing each icon opened a window that showed the probability of an event, and a fixed increase or decrease in journey time if the event took place. Costs related to obstruction of progress, due to terrain and mechanical breakdown. Selection of a cost icon, for example, might have specified a 10% probability of damage to the snowcat due to rough terrain, leading to a time increase of 20 min. Conversely, benefits related to enhanced performance of the snowcat, short-cuts and weather improvements, leading to decreases in journey time. For example, there might have been a 20% probability of finding a short cut to reduce the journey, leading to a time decrease of 10 min. After assessing the costs and benefits of each route, the participant chose one of the two, using the mouse to register the choice of route. A time limit of 15 s was imposed for each item; after this time, access to the cost and benefit information was disabled, and a message requesting immediate response was presented.

In principle, participants could make a rational decision by calculating the expected travel times for each route. In this study, optimization of route choice was not of interest, and so the expected travel times were equal for each route. Similar to Matthews et al. (2011), routes differed qualitatively. One route provided small but probable benefits and large but improbable costs, whereas the other presented likely small losses and unlikely large benefits. 'Probable' events varied in likelihood from 0.67 to 0.80; 'improbable' events from 0.15 to 0.33. 'Small' events imposed time costs or benefits that varied from 3 to 16 min whereas 'large' events were associated with values of 18–36 min. Matthews et al. (2011) found that participants generally preferred the 'small but probable benefit' route, interpreted as a loss-aversion effect consistent with prospect theory (Kahneman et al. 1982). The major focus of the present study was on information search rather than on route choice. The qualitative difference between routes was retained to test whether the bias in choice was sensitive to positive and negative affect.

Mood induction

Participants were randomly assigned to either a positive feedback or negative feedback condition. Feedback was given after each route choice by two screens following each item. The first screen contained a graphic signaling

Fig. 2 Sample feedback screen for a positive outcome

which event had occurred (i.e., cost-related or benefit-related), and a statement of how much time had been lost or gained (Fig. 2). A second feedback screen followed which described cumulative time lost or gained across all trials, with a graphic of either an unhappy or happy explorer. The outcome of each route choice was predetermined so that participants in the negative feedback condition would experience predominantly negative events, losing time, whereas in the positive feedback condition, most outcomes were positive, speeding travel. The present task had a total of 30 items, so that there were a total of 60 routes. In the negative feedback condition, 36 routes were associated with a negative outcome, 18 with a positive outcome, and 6 with 'no event'. In the positive feedback, proportions of positive and negative outcomes were reversed.

Though the overall outcome was manipulated, the precise cumulative gain or loss of time thus varied according to the participant's choices. In the negative feedback condition, mean total time lost was 156 min (range: 39–253; SD = 42), whereas in the positive feedback condition, mean total time gained was 143 min (range: 14–252; SD = 49). Thus, the two conditions were approximately matched for magnitude of time lost or gained.

Design and procedure

A between-groups design was used with feedback as the between-subjects factor; participants were randomly assigned to either the success or failure condition. All participants completed the EPQ-R and STPI (trait), followed by a baseline, pre-task mood assessment using the PANAS and STPI (state). Participants then completed a short training session on the 'search-and-rescue' decision-making task, which included a Powerpoint instruction presentation followed by a three item practice session with feedback, approximately 10 min in duration. Next, they performed the main task (30 items), during which either predominantly positive or predominantly negative feedback was delivered. Mood was again assessed post-task, using PANAS and STPI. The NASA-TLX was also administered. Individuals who were assigned to the failure feedback condition were offered a positive mood induction after debriefing.

Results

Results were analyzed as follows. First, as manipulation checks, we tested for effects of feedback on the affective dimensions, and on components of mental workload. Second, we analyzed for relationships between independent variables and frequencies of sampling the benefit and hazard icons, taken as indices of attention. An initial analysis of effects of feedback and time on task was followed by regression analyses in which the affective scales were included as predictors. These analyses provide the primary tests of hypotheses derived from the selective attention bias and mood-as-input models. Third, we analyzed for effects of independent variables on choice of route, to check whether any biases in information-search impacted decision. Finally, we tested for effects of the personality traits linked to emotionality, on affective response to the decision-making task, and the indices of decision-making performance.

Manipulation checks

Success and failure manipulation effects were assessed using 2 × 2 (pre/post task × feedback condition) mixed-model ANOVAs. The first, repeated-measures factor refers to pre-task and post-task state measurements. Two separate ANOVAs were run for (1) the NA and PA scales of the PANAS and (2) the state anxiety, anger and depression scales of the STPI. The interaction between pre/post and feedback condition tests whether there was differential state change across the two feedback conditions. In the first ANOVA, the pre/post × feedback interaction was significant for NA, $F(1,58) = 49.24$, $\eta_p^2 = 0.238$, $p < .01$, and for PA, $F(1,58) = 64.24$, $\eta_p^2 = .289$, $p < .01$. In the second ANOVA, the pre/post × feedback interaction was significant for depression, $F(1,58) = 13.60$, $\eta_p^2 = 0.079$, $p < .01$, and for anger, $F(1,58) = 30.04$, $\eta_p^2 = 0.160$, $p < .01$. The interaction approached significance ($p = .056$) for anxiety, $F(1,58) = 3.70$, $\eta_p^2 = 0.023$. Follow up t tests comparing pre- and post-task state ($df = 79$) showed that in the positive feedback condition there was a significant increase in PA, $t = 2.22$, $p < .05$, and a significant decrease in NA, $t = 3.71$, $p < .01$. In the negative feedback condition, PA declined, $t = 8.79$, $p < .01$, and NA, anxiety, depression and anger all increased, ts = 6.13, 4.00, 6.45, 6.00, respectively, $ps < .01$. Means and SDs for the state measures pre- and post-task are shown in Table 2. In the positive feedback condition, a modest increase in PA was accompanied by a small decrease in NA. In the negative feedback condition, larger-magnitude increases in NA and the STPI negative emotions and decrease in PA were obtained. Thus, feedback was effective in changing mood, but larger magnitude state changes were seen with negative feedback.

We also tested for feedback effects on mental workload, using the 6 scales of the NASA-TLX. In general, mental workload was substantial, with the highest ratings obtained for effort ($M = 6.64$, SD = 2.18), mental demands ($M = 6.18$, SD = 1.99), and temporal demands ($M = 5.78$, SD = 2.79). These ratings confirm that participants were generally engaged with the task. Bonferroni-corrected t tests were used to compare workload ratings in the two conditions. Mean ratings were higher in the negative feedback condition for temporal demands, $t(158) = 2.75$, $p < .05$: means 6.32 versus 5.31, and for frustration, $t(158) = 10.20$, $p < .01$: means 6.27 versus 2.30. Ratings of performance were higher in the positive feedback condition, $t(158) = 2.75$, $p < .01$: means 9.06 versus 2.25. The feedback manipulation changed perceptions of the task consistent with expectation, although there was no effect of the manipulation on either mental demands or effort.

Table 2 Means (and SDs) for pretask and posttask state scores in positive feedback and negative feedback groups

State scores	Positive feedback group		Negative feedback group	
	Pretask	Posttask	Pretask	Posttask
PANAS scales				
Positive affect	29.70 (7.8)	31.23 (8.8)	29.90 (7.6)	23.12 (7.8)
Negative affect	12.02 (2.5)	11.29 (2.1)	12.75 (3.1)	15.72 (4.9)
STPI scales				
Anxiety	14.87 (4.1)	15.63 (4.0)	16.86 (4.8)	18.87 (4.5)
Anger	11.16 (3.1)	11.06 (3.2)	10.89 (2.3)	14.46 (5.8)
Depression	15.32 (3.9)	15.77 (3.4)	15.90 (3.5)	18.99 (5.0)

Attention to hazards and benefits

We tested whether the feedback manipulation influenced frequencies of sampling the hazard and benefit icons, and whether any bias in sampling changed over time. To test for temporal effects, data from the 30 trials were analyzed as six successive blocks of 5 items each, using a 6 × 2 × 2 mixed-model ANOVA (block × feedback condition × icon type). The effect of icon was significant, $F(1,158) = 4.30$, $\eta_p^2 = 0.027$, $p < .05$. Benefits were sampled more frequently than hazards. Total sampling frequency across all 30 items was 79.5 (SD = 18.9) for benefits, and 75.9 (SD = 19.8) for costs. However, there was also a significant main effect of block, $F(5,790) = 6.85$, $\eta_p^2 = 0.042$, $p < .01$, and a significant block × icon type interaction, $F(5,790) = 4.47$, partial $\eta^2 = 0.027$, $p < .01$. Sampling frequencies tended to decline over time, especially for benefit icons. In the first block, sampling frequency was higher for benefits than for costs (means: 14.4 vs. 12.8), and the difference in means was significant, $t(159) = 4.51$, $p < .01$. In the final block, the corresponding means were 12.6 and 12.5, which did not differ. Of most relevance, there were no significant main or interactive effects of the feedback manipulation.

To test for individual differences in attention, we first calculated the reliability (α) of the frequencies for sampling hazard and benefit icons, across the six phases of the task: αs were 0.866 for benefit icon frequency and 0.876 for hazard icon frequency. Thus, participants appeared to show consistent biases throughout the task. On this basis, we calculated total frequencies of sampling the two kinds of icon for the whole task. Participants were free to sample each icon as often as they wished in the time available, so total frequencies might exceed the total number of icons presented. Multiple regression analyses were run with these two overall frequency measures as criteria. Separate regressions were run using (1) the two PANAS scales and (2) the three STPI negative emotion scales as predictors. Post-task measures were used for these analyses, as being more representative of mood during performance than the pre-task measures which preceded delivery of feedback. These regressions were also used to test for interaction between affect and feedback group. Continuous variables were centered. Feedback group was effect-coded as (1) for positive feedback and (−1) for negative feedback. Interactions between each affect scale and feedback group were then calculated as product terms. Three-step hierarchical regressions were then run, entering group, affect scales, and group × affect interaction terms, in turn.[1] The two regressions run with benefit icon frequency as the criterion were significant for both the analysis including the PANAS scales, $R = 0.342$, $F(5,154) = 4.08$, $p < .01$, and for the analysis with the STPI scales as predictors, $R = 0.370$, $F(7,152) = 3.45$, $p < .01$. In each case, the first two steps (feedback, linear affect scales) failed to add significantly to the variance explained (see Table 3). However, the product terms contributed significantly to the equation for both the PANAS and STPI regressions, implying that the relationship between affect and search of benefit icons varies across feedback group. The regressions for hazard icon frequency were both non-significant.

Table 4 gives the β values for the final equations. For the PANAS equation, the contribution of the linear NA term was significant, as well as both interaction terms. For the STPI equation, none of the linear predictors attained significance, but the anxiety × feedback and depression × feedback terms were both significant. Table 4 also gives variance inflation factors (VIFs), which may be used as diagnostics for collinearity (Pedhazur 1997). Collinearity is a potential concern because of the intercorrelation of the STPI state affect scales (range of *r*s: 0.41–0.63). VIFs greater than 1.0 indicate some inflation of the standard errors of the regression coefficients, but in these data, VIFs fall considerably short of the arbitrary value of 10 which may indicate a problematic level of collinearity.

To visualize the PANAS interactions, Fig. 3 shows the plots of sampling frequency against PA for each feedback condition that are predicted by the regression equation (using unstandardized regression coefficients: Aiken and West 1991). PA is expressed as a *z*-score axis and NA is set to zero. It shows that, with increasing PA, frequency of sampling benefit information increases in the negative feedback condition, but decreases in the positive feedback condition. Figure 4 shows the corresponding graph for sampling frequency as a function of NA, with PA set to zero. In this case, NA appears to have little effect on sampling in the negative feedback condition, but relates negatively to sampling the benefit icon in the positive feedback condition. Because the analyses of the STPI are subsidiary to the PANAS analyses, we do not present corresponding graphs for anxiety and depression. In general, though, the signs of the regression coefficients indicate that (like NA) anxiety tended to be positively related to benefit search in the negative feedback condition, but negatively related to benefit search in the positive feedback condition. Conversely, depression tended to be associated

[1] This analysis depends on there being sufficient variability in affective state within each feedback group to differentiate effects of group from effects of affect. Comparison of pre-task and post-task SDs in Table 1 shows that the feedback manipulation did not produce any restriction of range. In addition, although post-task means differed across groups, there was considerable overlap in the distributions of each state across positive and negative feedback conditions.

Footnote 1 continued

Table 3 Summary statistics for regressions of benefit sampling frequency onto two sets of affect scales

	PANAS			STPI		
Step	ΔR^2	*df*	*F*	ΔR^2	*df*	*F*
1. Feedback	0.003	1,158	0.42	0.003	1,158	0.42
2. State variables: linear terms	0.007	2,156	0.53	0.005	3,155	0.26
3. State × feedback interaction terms	0.108	2,154	9.38**	0.129	3,152	7.59**

** $p < .01$. PANAS state variables were PA and NA. STPI state variables were anxiety, anger and depression

Table 4 Regression coefficients and VIFs for prediction of benefit sampling frequency from two sets of affect scales

Criterion	Predictor	β	VIF
PANAS	Feedback	0.07	1.84
	PA	−0.04	1.28
	NA	−0.27*	2.69
	PA × feedback	0.30**	1.03
	NA × feedback	0.24*	2.00
STPI	Feedback	−0.09	1.29
	Anxiety	0.14	1.91
	Anger	−0.11	1.98
	Depression	0.07	1.95
	Anxiety × feedback	0.24*	1.66
	Anger × feedback	0.14	1.75
	Depression × feedback	−0.46**	1.71

* $p < .05$, ** $p < .01$

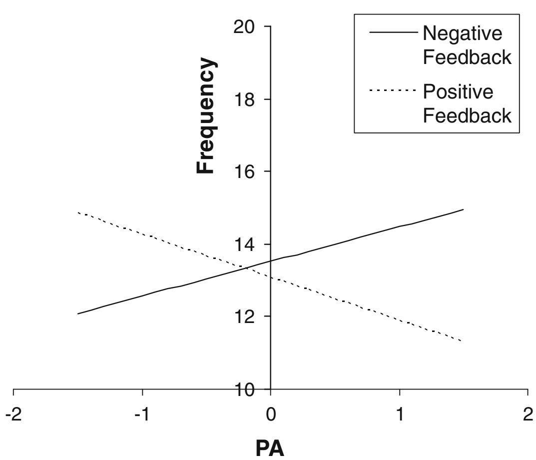

Fig. 3 Predicted sampling frequencies for benefits as a function of PA, in negative and positive feedback conditions

with reduced search for benefits under negative feedback, but increased search when feedback was positive.

Route choice

Effects of feedback condition and trial block on route choice were analyzed using a 2 × 5 mixed-model

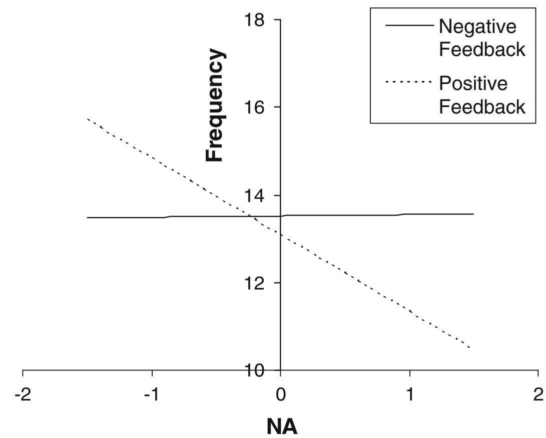

Fig. 4 Predicted sampling frequencies for benefits as a function of NA, in negative and positive feedback conditions

ANOVA. The main effect of feedback was significant, $F(1,158) = 5.94$, $\eta^2 = 0.036$, $p < .05$, but the effects of block and the feedback × block interaction were non-significant. The mean for choice of the 'high probability/small benefit' option was higher in the positive feedback condition ($M = 56.1\%$, SD = 27.3), than in the negative feedback condition ($M = 47.6\%$, SD = 15.6). Thus, feedback appeared to affect strategy for route choice, but the effect was stable throughout performance. The bias towards preferring a likely small benefit seen in the positive feedback condition is consistent with findings of Matthews et al. (2011); the mean for the negative feedback condition did not differ significantly from 50 (i.e., zero bias) on a 1-sample t test. Possibly, participants in the negative feedback condition felt encouraged to gamble on obtaining a low probability large benefit to offset their losses in time, offsetting the bias evident with positive feedback. Correlations between trait and state variables and route choice were calculated, but no associations reached significance.

Personality analyses

Prior to testing whether personality traits related to decision-making performance, we investigated relationships between the personality variables of E and N and affect. Five multiple regressions were run, using the two PANAS and three STPI state dimensions as criteria. Regressions were run in three steps, including, in turn, (1) feedback group, (2) E and N, and (3) the centered product terms, E × feedback, and N × feedback. These regressions were significant at $p < .01$ for all five criteria: PA ($R = 0.513$), NA ($R = 0.589$), anxiety ($R = 0.458$), anger ($R = 0.437$) and depression ($R = 0.502$). In each case, feedback group contributed significantly ($p < .01$) to the equation, consistent with the ANOVAs previously reported (range of ΔR^2 values: 0.255–0.117). In each case too, the linear personality terms added significantly ($p < .01$) to the variance explained (range of ΔR^2 values: 0.114–0.054). N was the more consistent personality predictor; this trait contributed significantly ($p < .01$) to the final equations for all affective dimensions except positive affect. βs in the final equations were 0.241 (NA), 0.263 (anxiety), 0.228 (anger) and 0.255 (depression). The only significant effect of E was obtained in the analysis of PA ($\beta = 1.96$, $p < .01$). Inclusion of the product terms tests whether the relationship between the trait and state concern was moderated by feedback condition. In fact, in no cases was the joint contribution of the two product terms significant. In the NA regression, the β of 0.132 for the N × feedback interaction was significant ($p < .05$), suggesting that more neurotic individuals responded to negative feedback with greater negative affect, as hypothesized. However, this finding should be interpreted with caution given the non-significance of the contribution of the block of product variables.

Effects of E and N on the decision-making performance indices were analyzed similarly to state effects, using a regression approach. Three-step hierarchical regressions were then run, entering feedback group, the two trait scales, and group × trait product terms, in turn. With frequency of sampling benefit icons as the criterion, the regression equation was significant, $R = 0.262$, $F(5,159) = 2.26$, $p < .05$. Only the second of the three steps (entry of linear trait terms) attained significance, $\Delta R^2 = 0.044$, $F(2,156) = 3.62$, $p < .05$. The βs of -0.16 for E and -0.16 for N were both significant at $p < .05$. Both extraverts and individuals high in N tended to sample benefits less frequently. The equations for sampling of hazard icons and for actual route choice were both non-significant.

Finally, we found expected correlations between corresponding post-task STPI state and trait scores of 0.18 ($p < .05$) for anger, 0.34 ($p < .01$) for anxiety, and 0.43 ($p < .01$) for depression. However, the STPI trait scores were unrelated to information search.

Discussion

Several findings matched our broad expectations for (1) effects of feedback on emotion, (2) associations between emotion and information search, and (3) personality effects on emotion. Specifically, the feedback manipulation was successful in altering emotional state in the appropriate directions, although the effect of the negative feedback manipulation was stronger than the positive one. Similar to the results of Matthews et al. (2011), emotion and personality influenced the search for information but not the actual decisions made, adding to evidence that affective variables may bias the attentional components of decision-making. However, emotions had no intrinsic effect on information search, across conditions. In fact, correlations between affect and information search were quite strongly dependent on the context provided by the feedback. Findings are thus consistent with the contemporary emotion theories that emphasize the role of context in moderating associations between affect and information-processing (Clore and Huntsinger 2009; Das and Fennis 2008). Associations between personality and emotion were broadly as predicted, but E and N failed to show any mood-congruent associations with information search. In the remainder of this discussion, we examine the theoretical implications of these key findings further.

The importance of context: Theoretical implications

Initially, we suggested two possible rationales for predicting effects of emotion on information search. Consistent with the general mood-congruence principle (Bower 1981), the selective attention bias hypothesis (Mathews and MacLeod 2005) predicts that emotion may bias search through influencing which icons tend to capture attention. However, contrary to the prediction, there was no general tendency for negative feedback to enhance attention to hazard icons, or for positive affect to be related to frequency of sampling potential benefits. Indeed, we found no predictors of search for hazard icons. Mood-congruence was found only within specific contexts, such as the positive association between PA and search for benefits in the negative feedback condition. These data do not suggest the operation of an automatic bias related to emotion (Bar-Haim et al. 2007; Mathews and MacLeod 2005). If threat stimuli automatically capture attention in states of negative emotion, or if the unhappy person cannot disengage attention from sources of threat (Fox et al. 2002), such processes would be expected to operate irrespective of feedback. Selective attention bias may be more reliable for anxiety rather than negative emotion in general (e.g., Mogg and Bradley 2005), but we also failed to find any linear association between state anxiety and sampling of the threat icon. Additionally, trait anxiety was unrelated to bias in sampling. Matthews et al. (2011) suggest that uncertainty over one's performance may be critical for observing anxiety effects on information search in the present task paradigm. Feedback, of course, reduces uncertainty.

Two features of the design may have limited mood-congruent processing. First, the icon stimuli used had, at most, only mild intrinsic affective content; their valences derived from the task context, as in many real-life decision-making contexts. Possibly, stimuli with stronger intrinsic valence, such as happy and fearful faces, would have elicited mood-congruence in search. Second, we did not analyze temporal patterns of visual search that might have revealed more subtle forms of mood-congruence, such as the order in which icons were searched.

On the basis of the mood-as-input hypothesis (Martin 2001), we predicted that positive mood should relate positively to search for benefit icons in the negative feedback condition (signaling courage in adversity) but the association should be negative in the positive feedback condition (signaling easy accomplishment of task goals). This prediction was confirmed. We also predicted interactive effects of NA and feedback condition on frequency of sampling cost icons, on the basis that the meaning of negative moods may change with success versus failure, but this prediction was not supported. Instead, NA interacted with feedback condition to influence attention to benefits, independently from the effect of PA. Indeed, attention to benefits was generally more sensitive to affect than attention to costs.

Although we obtained only partial support for the specific predictions derived from the mood-as-input hypothesis, the data provide additional confirmation for the growing trend in emotion theory to see affective bias as dependent on the personal interpretations placed on affective states, rather than on invariant linkages between affect and information-processing (Bless and Fiedler 2006; Clore and Huntsinger 2009). The open question is the extent to which general principles for deriving meaning from affective states can be established. The mood-as-input hypothesis (Martin 2001) is the most radical departure from traditional mood-congruence in that it denies any intrinsic effect of emotions on processing. By contrast, Clore and Huntsinger (2009) suggest that bias reflects general principles derived from the mood-as-information hypothesis; positive and negative affects confer value on accessible processing tendencies. The accessibility of processing is dependent on contextual factors, including attributional processes, and so emotions do not necessarily produce fixed biases. We focused here on mood-as-input theory because it directly addresses decisions to stop or continue processing (Martin et al. 1993), which are known to be critical for information search (Browne and Pitts 2004). However, other theories that allow for contextual moderation of affective bias might also provide explanations for bias in information search.

Additional theoretical implications

The interpretation of the data in terms of the mood-as-input theory (Martin 2001) is broadly compatible with other theories that are concerned with how the motivational implications of mood states may vary. Fishbach et al. (2010) propose that feedback effects on goal-directed behavior are dependent on the person's understanding of the emotions elicited by the feedback. Specifically, task motivation varies according to whether emotion is interpreted as signaling commitment to the task goal (increases motivation) or that sufficient progress is being made (decreases motivation). A student who receives a good grade on a math test may increase subsequent efforts if her positive emotions are interpreted as a sign of high commitment, or she may decrease them, if the emotion signals that progress is adequate (see also Orehek et al. 2011). In the current study, positive affect may be interpreted as a signal of continuing task commitment in the negative feedback condition ("courage in adversity") but as a signal of sufficient progress ("easy accomplishment") in the positive feedback condition.

Positive affect may serve as a resource for facing up to potentially discomforting information, provided that it is diagnostic and self-relevant (Trope et al. 2001; Trope and Pomerantz 1998). Trope and Neter (1994) showed that mood inductions could produce mood-incongruent information search; for example, participants who initially recalled positive life events were more likely to subsequently seek information about their weaknesses than their strengths, following performance of a social sensitivity task. Similarly Das and Fennis (2008) showed that positive mood promoted systematic processing of personally threatening health-related information. In the current study, negative feedback may have increased the self-relevance of the task, so that positive affect promoted a more active search of benefit icons (although we might also have expected a similar effect on search of cost icons).

Conversely, the data are incompatible with other theories of mood and cognition that suggest context-invariant influences of mood on motivations to continue or cease information search. According to the mood-repair hypothesis, people are motivated to repair negative moods and maintain positive moods (Isen 1993), so that task performance may be influenced by the strategies used for mood-regulation. Reflecting on positive experiences as a strategy for relieving an unpleasant mood may explain mood-incongruence in memory (Joormann and Siemer 2004; Smith and Petty 1995), and in self-appraisals and social judgments (McFarland et al. 2007). The mood-repair hypothesis suggests that negative mood might lead to a bias towards attending to positive icons. Presumably, the person would be motivated to repair negative mood regardless of success or failure context. However, the regression analysis suggested that NA was unrelated to sampling of benefit icons in the negative feedback condition, and negatively related to benefit sampling in the positive feedback condition. These findings provide little support for the mood-repair hypothesis.

Another influential idea is that positive moods promote unsystematic, heuristic processing that requires relatively little effort, whereas negative moods lead to more thorough, systematic processing (see Bless and Fiedler 2006). This theory predicts that negative mood should be associated with generally more extensive information search than positive mood, regardless of icon content and context. Again, the findings do not support the hypothesis. PA was associated with more extensive search of benefit icons in the failure condition, and NA was associated with reduced search of benefit icons in the success condition. There appears to be no simple association between affect and the level of effort applied to information search.

Subsidiary hypotheses

The study also investigated possible biases associated with specific negative emotions, and with traits for positive and negative affectivity. The regression analysis of STPI state variables suggested that interactions with feedback varied across the different negative emotions. The anxiety × feedback interaction was similar to the NA × feedback interaction. However, the β for the depression × feedback interaction was negative in sign, suggesting that in the negative feedback condition depression related negatively to search for benefits, but in the positive feedback conditions depression correlated positively with search for benefits. This finding conflicts with the mood-repair hypothesis (Isen 1993; McFarland et al. 2007) in that depressed mood might motivate a search for positive-valent information following negative feedback. In fact, depression effects may correspond to those found with PA, given that depression typically relates to low PA. The correlations between PA and depression were −0.56 before task performance and −0.41 afterwards, whereas those between NA and depression were 0.43 and 0.30, respectively. Thus, there may be one mood effect associated with NA/anxiety and a separate effect associated with PA/low depression. Depressed individuals may be less likely than those low in depression to interpret positive mood as a sign of easy accomplishment following success.

Linear associations between personality and emotional state were consistent with expectation, in that E was positively associated with PA, and N with NA and other negative emotions. Similar results have been found in numerous studies (Lucas and Diener 2000; Amin et al. 2004). However, moderation of these associations by feedback conditions was weak. Some evidence was found for a stronger association between N and NA in the negative feedback condition, but we did not find that E relates more strongly to PA under positive feedback. Results are thus consistent with Lucas and Baird's (2004) conclusion that N is more strongly related than is E to mood reactivity, and various studies showing that E is rather weakly associated with PA in controlled performance environments (Matthews et al. 2009). In addition, only specific facets of E may relate to positive mood response (Morrone-Strupinsky and Lane 2007). We also failed to show any feedback-dependent effects of personality on information search, although both E and N were negatively associated with search for benefits. These associations differ from the predictions that E should relate positively to search for benefits whereas N should be associated with search for costs. Thus, as with the emotion data, there is little evidence for mood-congruent processing associated with trait emotionality factors in the present task paradigm.

Limitations

Several limitations of the study should be noted. The present results may be limited by use of an artificial laboratory paradigm. It is unclear whether findings would generalize to real-life decision-making, although the search-and-rescue task is typically immersive and engaging for participants (Matthews et al. 2011). In addition, there may be fine-grained interaction between affect and sampling strategy, perhaps even on a trial-by-trial basis. The current methodology is not suitable for investigating such processes. While the major theories of interest suggest effects of mood state on search strategy, search strategy might also affect mood. A more fine-grained investigation might be necessary to arrive at strong causal conclusions, and any causal implications drawn from the current data are necessarily tentative.

Another issue is that the task itself may have imposed stress due to its complexity and time pressure, confirmed by high ratings on the NASA-TLX scale. High workload is reliably related to emotional distress during task performance (Matthews et al. 2002). Although negative and positive feedback manipulations are normally equally efficacious as mood-inducers (Nummenmaa and Niemi 2004), we obtained larger effect sizes for negative feedback, suggesting that feedback effects may have been overlaid on top of task-induced negative affect. This suggestion may explain why search for benefits appeared to be more sensitive to affect than search for costs. With this task, NA may have been interpreted as a direct consequence of high mental workload, and so discounted in decisions over whether or not to continue searching for threats. By contrast, PA was less intrinsic to the task environment. The context of success or failure appears to have shaped the person's interpretation of their positive feelings, and, in consequence, their willingness to explore possible benefits to routes more or less thoroughly.

Finally, the derivation of predictions from the mood-as-input model (Martin 2001) relies on the inferences made about participants' understanding of emotions in the different conditions as expressed in Table 1. Although the model is promising, these inferences are tentative and require further substantiation. Some of the recent work we have cited (e.g., Fishbach et al. 2010) has begun to investigate the different meanings that may be assigned to emotional response during task performance, but more remains to be done, including development of methods for assessing the meanings of emotions within different performance contexts.

Conclusion

Individual differences in emotion relate to information search, but the associations found were rather unstable. In naturalistic settings, such as internet search, decision-makers may be vulnerable to over-scrutiny or to neglect of emotionally-laden information in some circumstances, but the nature of the affective bias is more complex than suggested by the mood-congruence hypothesis. Context-dependence of affective bias in information search broadly supports the mood-as-input theory (Martin 2001) and other recent emotion theories (Bless and Fiedler 2006; Clore and Huntsinger 2009). Data are also compatible with the notions that relationships between emotion and motivation depend on how task-elicited emotion is interpreted (Fishbach et al. 2010), and that positive affect may act as a resource for dealing with negative self-referent information (Trope et al. 2001). Conversely, the findings are incompatible with theories that posit fixed associations between affective states and information-processing. Specifically, the data were incompatible with the selective attention bias hypothesis (Mathews and MacLeod 2005), which suggested that icons congruent with mood state would automatically draw attention to themselves. The data are also inconsistent with the hypotheses that negative mood may divert processing towards positive-valent items as a repair strategy (Smith and Petty 1995) and that negative moods may promote more systematic, exhaustive search (Bless and Fiedler 2006).

Our results do not invalidate the theories whose hypotheses were not confirmed (e.g., selective attention bias), but they suggest that these hypotheses may only be relevant to certain task paradigms. One of the challenges for emotion research may be to determine the boundary conditions defining the applicability of each theory. The present task required the participant to use positive- and negative-valenced information in support of decision-making; i.e., the information was directly relevant to action. By contrast, studies supporting the mood-congruence principle, including the classic demonstrations that anxiety relates to selective attentional bias to threat, typically place the person in the passive role of doing no more than encoding and discriminating stimuli. Use of valenced information in decision may require a more flexible assignation of meaning to emotion than does passive encoding.

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