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Enhanced avoidance learning in behaviorally inhibited young men and women

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(Received 6 July 2012; revised 23 October 2012; accepted 24 October 2012)

Abstract

Behavioral inhibition (BI) is a temperamental tendency to avoid or withdraw from novel social and nonsocial situations, and has been shown to predispose individuals to anxiety disorders. However, adequate means to assess individual differences in avoidance learning in humans are presently limited. Here, we tested whether individuals with high self-reported BI show faster associative learning on a purely cognitive task and whether such inhibited individuals are more prone to avoid aversive outcomes. In Experiment 1, we tested 74 healthy undergraduate students (mean age 19.5 years; 55.4% female) on a computer-based probabilistic classification task, where participants were asked to classify four distinct visual stimuli into two categories. Two stimuli were associated with reward (point gain) and two were associated with punishment (point loss). In Experiment 2, 79 participants from the same population (mean age 19.8 years; 62% female) were tested on a novel modification of the same task, where they also had the option to opt out of responding on each trial, thus avoiding any chance of being punished (or rewarded) on that trial. Results show that inhibited participants demonstrated better associative learning in Experiment 1, while exhibiting a greater tendency to opt out in Experiment 2 (repeated-measures analysis of variance, main effects of BI, both $p < 0.05$). These results indicate that the facilitated classically conditioned learning previously observed in inhibited individuals can be extended to a cognitive task, and also highlight a specific preference in inhibited individuals for withdrawal (“opting out”) as a response strategy, when multiple strategies are available to avoid punishment.

Keywords: Anxiety disorders, associative learning, behavioral inhibition, classification task, decision-making, probabilistic task

Introduction

Decision-making is probably one of the most important challenges that one faces daily, and it provides crucial feedback that directly affects future choices. There are two distinct behavior strategies that ideally should be employed together, in order to maximize benefit and minimize loss; individuals can learn and repeat actions that were rewarded in the past, or alternatively they can avoid actions that are associated with past loss (Wachter et al. 2009). Yet, these strategies are not equivalent with regard to

adverse mental health outcomes; the tendency to avoid may have implications for anxiety and the development of anxiety disorders.

Avoidance is a common symptom of all anxiety disorders (DSM-IV; American Psychiatric Association 1994), and its severity parallels the overall growth and persistence of some of the disorders. For example, after exposure to a traumatic event, the degree of avoidance behavior differentiates those who develop posttraumatic stress disorder (PTSD) and those who recover (North et al. 1999; Karamustafalioglu et al. 2006; Marshall et al. 2006; O'Donnell

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et al. 2007). Although there is a growing appreciation that personality can shape an individual's tendency to avoid, and despite the direct relevance of avoidance to anxiety disorders, assessment of human avoidance behavior has been limited (Dymond and Roche 2009). In an experimental setting, avoidance can be assessed by measuring an individual's ability to learn to avoid or escape physically aversive stimuli, such as electric shock (Delgado et al. 2009), or aversive visual and auditory stimuli such as loud noises or unpleasant pictures (Dymond et al. 2011). Research has also been extended to computer-based tasks where the aversive outcome is point loss or monetary loss (Molet et al. 2006; Declercq and De Houwer 2008; Schlund and Cataldo 2010). However, since these tasks are often designed so that avoidance is the only possible way to prevent the aversive outcome, participants who perform well might simply be demonstrating facilitated associative learning, rather than a tendency to acquire avoidance behaviors in preference to other kinds of responses; tools to dissociate these two behavior aspects are lacking.

Behavioral inhibition (BI), a vulnerability factor for anxiety disorders (Rosenbaum et al. 1993), is a relatively stable personality trait conferring a tendency to avoid or withdraw from novel social and nonsocial situations (Kagan et al. 1989). A recent study showed a correlation between self-reported BI score and self-reported PTSD avoidance symptoms in veterans (Myers et al. 2012c). Moreover, inhibited individuals learn faster than their uninhibited peers on a classical eyeblink conditioning paradigm, where a conditioned response (eyeblink) is produced by a conditioned stimulus (tone) that predicts an aversive unconditioned stimulus (airpuff) (Myers et al. 2012b). Research with animal models of BI has also shown enhanced learning by inhibited subjects of both an operantly conditioned avoidance response (Servatius et al. 2008) and a classically conditioned eyeblink response (Ricart et al. 2011). However, much less is known about how BI might modulate associative learning where the outcomes are not physically aversive stimuli such as airpuffs, but rather on-screen feedback such as point loss in a computer task. In particular, rather than promoting a specific type of learning or response (e.g. acquiring somatomotor responses that promote avoidance of an aversive stimulus), individuals with inhibited temperament may show nonspecific enhancement in associative learning. It is also unknown whether individuals with inhibited temperament exhibit different behavior patterns than uninhibited peers on tasks that involve probabilistic and/or ambiguous contingencies. Ambiguous contingencies might lead to uncertainty, which can lead to significant anxiousness, especially among those who are intolerant for such feelings (Buhr and Dugas 2002). It is possible that inhibited individuals

will show higher tendency to avoid such uncertain situations.

Therefore, the central questions addressed in this work are as follows: (1) Do inhibited individuals learn faster than uninhibited individuals on a cognitive task, where the aversive outcome to be avoided is merely point loss and the response–outcome contingencies are probabilistic and ambiguous? (2) If so, is this reflected in a general facilitation of learning in inhibited individuals, or is the facilitation selective to learning to avoid punishment, rather than learning to obtain rewards? To answer those questions, we used a computer-based probabilistic classification task that has previously been used to demonstrate individual differences (Bódi et al. 2009). This task interleaves trials in which participants learn to make a correct classification in order to obtain a reward (point gain) and trials in which participants learn to make a correct classification in order to avoid a punishment (point loss). In Experiment 1 (“Forced-Choice”), we utilized the task to test whether there are differences between behaviorally inhibited versus uninhibited healthy young adults on reward and punishment learning. We hypothesized that inhibited participants would outperform their uninhibited counterparts on the classification task, similar to what was shown in the previous eyeblink experiments. In Experiment 2 (“Opt-Out”), we considered a modified version of the task in which participants had the option to opt out of responding on any trial (rather than being forced to make a classification decision), and thereby avoid any chance of being punished (or rewarded) on that trial. We hypothesized that inhibited participants would show more opt-out responding than uninhibited participants, particularly on trials where a punishment outcome was possible. Such responses would indicate that the inhibited individuals not only show generally faster associative learning but also a specific preference to respond to the threat of aversive outcomes by withdrawal.

Methods

Participants

In Experiment 1, participants were 74 healthy young adults (Rutgers University undergraduates; mean age 19.49 years, standard deviation (SD) 1.55; 55.4% female), recruited via a departmental subject pool, in which available research studies are posted and students sign up to participate in exchange for research credits in a psychology class. Experiment 2 included 79 participants from the same institution (mean age 19.82 years, SD 1.62; 62% female). None had participated in Experiment 1. Most participants were recruited through the departmental subject pool, as for Experiment 1. However, an additional nine participants were recruited via flyers posted around

the campus and received cash payments in the amount of \$20. No difference on any behavioral, demographic, or questionnaire measure was observed between participants that received cash versus participants that received credits (all $p > 0.20$); analyses were therefore pooled over all 79 participants. In both experiments, procedures followed guidelines established by Rutgers University and the Declaration of Helsinki for the protection of human subjects. All participants provided written informed consent before initiation of any experimental procedures.

Procedure

Participants were tested individually; the participant and experimenter sat in a quiet testing area during the experiment. Participants completed the adult measure of behavioural inhibition (AMBI), a self-report questionnaire, which assesses current temperamental tendency to respond to new stimuli with inhibition and/or avoidance and has high internal consistency (Cronbach's $\alpha = 0.87$) and high test-retest consistency (intraclass correlation coefficient 0.86, $p < 0.001$), and has been shown to be a measure of anxiety proneness (Gladstone and Parker 2005). Individuals scoring < 16 are classified as "uninhibited," whereas individuals scoring 16 or higher are classified as "inhibited."

In addition, participants in Experiment 1 were administered a computer-based probabilistic classification task; full description of the task is given in Bódi et al. (2009). In brief, on each of 160 trials, participants viewed one of the four images (stimuli S1, S2, S3, and S4; Figure 1A), and learned whether it belonged to category A or category B. On any given trial, stimuli S1 and S3 belonged to category A with 80% probability and to category B with 20% probability; stimuli S2 and S4 belonged to category B with 80% probability and to category A with 20% probability. Stimuli S1 and S2 were used on reward-learning trials; if the participant made a correct

classification response, a reward of +25 points was received (Figure 1B) but if the participant made an incorrect classification response, no feedback message appeared. Stimuli S3 and S4 were used in punishment-learning trials; if the participant made an incorrect classification response on a trial with either of these stimuli, a punishment of -25 points was received, but correct classification received no feedback message. Thus, the no-feedback outcome, when it arrived, was ambiguous, as it could signal lack of reward for an incorrect response (if received during a trial with S1 or S2) or lack of punishment for a correct response (if received during a trial with S3 or S4). Participants did not receive any monetary reward related to point accumulation during the experiment.

Trials were divided into four blocks of 40 intermixed trials, with each stimulus appearing 10 times per block (for a total of 20 reward and 20 punishment trials intermixed per block).

Participants in Experiment 2 received the same task, except that on each trial, in addition to responding "A" or "B," the participant could choose a third option, "skip," which allowed the participant to opt out of responding on that trial. If the subject chose this option, the following acknowledgment appeared on the screen "OK, skipping this one..." and the program advanced to the next trial without further feedback and without point gain or loss.

Data analysis

Statistical analyses were conducted using SPSS version 17.0 (SPSS, Inc., Chicago, IL, USA). Alpha was set to 0.05 (two tailed), with Bonferroni correction used as appropriate to protect against inflated risk of family-wise error. Effects and interactions that did not approach significance were not reported (all $p > 0.10$). Questionnaire scores were analyzed using t -test for continuous values and chi-square for categorical values, with Yates continuity correction for 2×2 tables. Internal consistency of the AMBI questionnaire was analyzed using Cronbach's α .

In Experiment 1, for each participant and each trial, the computer recorded whether the participant's classification response was correct and whether it was optimal. For a reward trial, the response was correct if it resulted in point gain; for a punishment trial, the response was correct if it resulted in no point loss. For each stimulus, the response was optimal if the participant chose the category that was most often associated with that stimulus. For example, stimulus S1 belonged to category A on 80% of trials; thus, response "A" was always optimal for that stimulus, but it would only be correct (i.e. result in point gain) on 80% of trials, because on the remaining 20% of trials S1 would belong to category B. Percent optimal and total correct classification responses were calculated separately for reward and punishment-learning

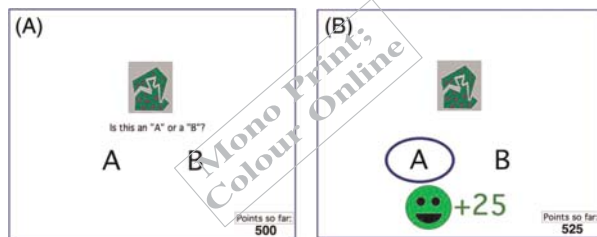


Figure 1. The feedback-based probabilistic classification task (Bódi et al. 2009). (A) On each trial, the participant saw one of the four stimuli and was asked whether this stimulus belonged to category A or B. Each stimulus belonged to one of the categories on 80% of trials and to the other category on 20% of trials. (B) For some stimuli, correct responses were rewarded with visual feedback and 25 points, whereas for other stimuli, incorrect responses were punished with visual feedback and the loss of 25 points.

335 trials. Repeated-measures analysis of variance (rmA-
NOVA) was used to assess responding, with between-
subject factor of BI (inhibited vs. uninhibited) and
within-subject factors of feedback type (reward vs.
punishment trials) and, in some cases, trial block (four
340 blocks of 20 trials with each feedback type). *Post hoc*
ANOVAs and *t*-tests were conducted, as appropriate.
When a correlation between continuous behavior
measures was made, a Pearson correlation coefficient
was used.

345 We carried out several further analyses to test
whether other cognitive factors could account for any
observed behavioral differences between BI groups.
First, we calculated a learning bias score for each
participant as the difference between percent optimal
classification responses on reward versus punishment
trials; calculation was done separately for the first and
the last blocks. Following Simon et al. (2010), we
350 defined “balanced learners” as those participants
whose absolute value of the bias score on the first
block was <25% (i.e. no strong difference in
performance on reward vs. punishment trials). Next,
we compared the stability of bias across the first versus
the last block. We defined “stable learners” as those
355 participants who had the same bias (balanced or
unbalanced) on the first and the last block. Pearson
chi-square was used to compare the distribution of
bias balance and stability between BI groups, with
Yates continuity correction for 2×2 tables.

360 To further investigate possible learning biases, we
considered trial-to-trial behaviors. Following previous
work (Frank and Kong 2008; Simon et al. 2010),
“win-stay” behavior was defined as the percentage of
trials in the first block on which the participant
365 repeated the response which was correct (i.e. either
rewarded or not punished) on the last trial where the
same stimulus appeared. “Lose-shift” behavior was
defined as the percentage of trials on which the
participant switched his or her response after making
an incorrect response (i.e. response that was punished
370 or not rewarded) on the last time the same stimulus
appeared. Pearson correlation coefficient was used to
analyze the correlation between win-stay and lose-shift
behaviors. We used rmANOVA to examine percent of
trials where participants displayed win-stay or lose-
375 shift behaviors, with BI as the between-subject factor
and behavior type (win-stay vs. lose-shift) as the
within-subject factor.

380 Lastly, response latencies in milliseconds were
assessed for each feedback type (reward vs. punish-
ment) and response (optimal vs. non-optimal). For
each participant, outlying values of latency (>3 SD
from mean) were excluded from the analyses. We used
rmANOVA on average latency, with BI as the
385 between-subject factor and response and feedback
type as within-subject factors.

In Experiment 2, for each trial, the computer
recorded whether the participant chose to opt out of

responding or, if not, whether the classification
response was correct and/or optimal. Dependent
variables were total number of opt-out responses to
reward and punishment stimuli, as well as percent
390 optimal and total correct classifications on those trials
where a classification response was made. However,
considering only percent optimal (or total correct)
classifications potentially obscures learning in partici-
pants who may have learned to make skipping
395 responses to punishment trials in order to minimize
risk of punishment. Therefore, we also considered a
measure of “adaptive responses” which included all
punishment trials on which either an opt-out response
or an optimal classification was made; for reward
400 trials, only optimal classifications were “adaptive
responses” since on these trials opting out would
cause omission of a possible reward. Participants were
also divided into “skippers” versus “non-skippers,”
where participants who made at least one opt-out
405 response during the experimental session were
categorized as “skippers.” Such “skipping” classifi-
cation was often included as a between-subject factor,
enabling comparison of performance between skip-
pers and non-skippers. Otherwise, data analysis was
410 similar to that of Experiment 1.

Results

Experiment 1: “Forced-Choice”

415 Mean score on the AMBI questionnaire was 13.4 (SD
4.56, Cronbach’s $\alpha = 0.73$). Twenty-two participants
(29.7%) were “inhibited.” There were no differences
in gender or age between BI groups (both $p > 0.30$).

420 Participants’ mean optimal classification perform-
ance on reward and punishment trials is shown in
Figure 2; inhibited participants outperformed unin-
hibited participants [rmANOVA, $F(1,72) = 4.620$,
 $p = 0.035$]. The main effect of trial block
425 [$F(3,216) = 12.84$, $p < 0.001$] was found, and the
interaction between trial block and BI was not
significant [$F(3,216) = 2.209$, $p = 0.088$]. Total cor-
rect responding for reward and punishment trials
revealed a similar main effect of BI [rmANOVA,
430 $F(1,72) = 5.574$, $p = 0.021$], with inhibited partici-
pants making more correct responses than uninhibited
participants; no other effects or interactions were found.

435 Next, we tested whether the differences between
inhibited and uninhibited participants could be
attributed to differences in learning bias (Figure 3).
In both BI groups, approximately 70% of participants
were balanced and a small majority of around 55%
were classified as stable learners (both $p > 0.80$).

440 There was also a negative correlation between
win-stay and lose-shift behaviors on the first block
($r = -0.544$, $p < 0.001$). Overall, participants showed
a higher percentage of win-stay than lose-shift

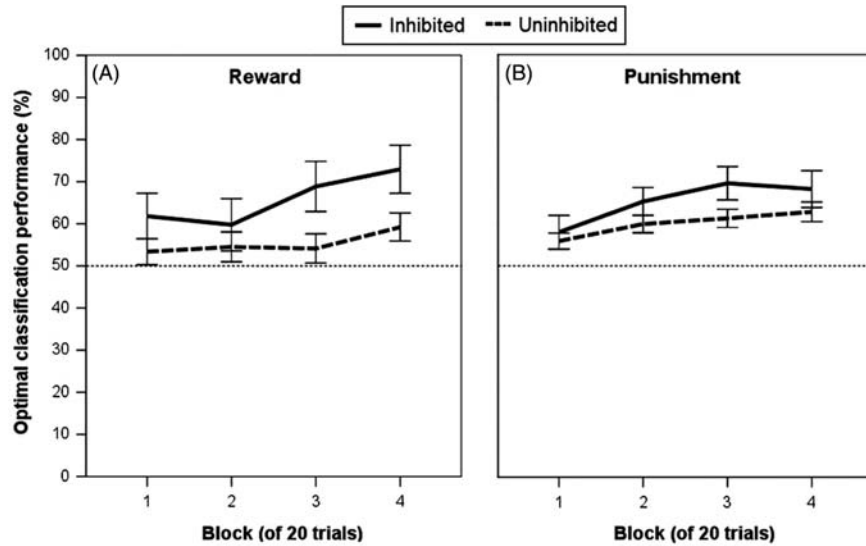


Figure 2. Mean optimal classification performance on (A) reward and (B) punishment trials in Experiment 1, in inhibited ($n = 22$) versus uninhibited ($n = 52$) participants. Both BI groups showed learning over blocks (rmANOVA, $p < 0.001$), but the inhibited participants outperformed their uninhibited counterparts ($p = 0.035$). Dotted horizontal line represents chance performance (50%). Error bars indicate SEM.

responses [$F(1,72) = 20.75$, $p < 0.001$], with no main effect of BI and no interactions (Figure 4).

Lastly, when latency was analyzed, one inhibited participant and one uninhibited participant were excluded as they did not have any non-optimal reward trials. Overall, participants had greater latency on punishment than on reward trials [$F(1,70) = 29.11$, $p < 0.001$] (Figure 5); the main effect of response was not significant [$F(1,70) = 3.472$, $p = 0.067$]. There was no effect of BI and no interactions.

Experiment 2: “Opt-Out”

Mean score on the AMBI questionnaire was 14.8 (SD 5.36, Cronbach’s $\alpha = 0.79$). Twenty nine of the

participants (36.7%) were classified as “inhibited” and 44 participants (55.7%) as “skippers.” In both BI groups, almost half of the participants did not show any skipping responses (Figure 6A). There were no significant differences in gender or age between BI groups, and no differences in gender, age or AMBI scores between skippers versus non-skippers (all $p > 0.30$).

Opt-out performance of participants classified as skippers is shown in Figure 6B,C. Inhibited participants skipped more trials overall than uninhibited participants [rmANOVA, $F(1,42) = 5.887$, $p = 0.020$]. There were also main effects of trial block [$F(3,126) = 17.74$, $p < 0.001$], with skipping behavior increasing over trial blocks, and feedback type

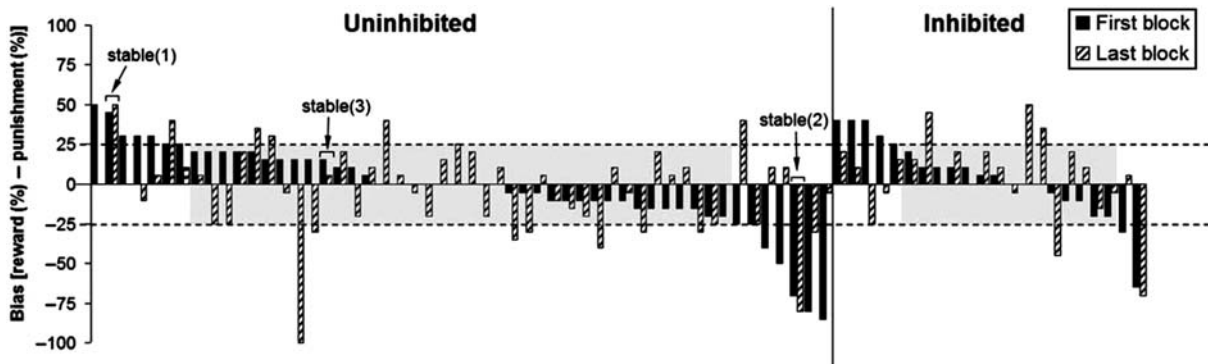


Figure 3. Individual bias scores (percent optimal on reward trials minus percent optimal on punishment trials), reflecting a participant’s bias to learn from either positive or negative feedback on the first and the last block of Experiment 1. Each pair of adjacent bars represents an individual participant. Within each BI group, participants are ordered by the magnitude of their bias on the first block. Blank spaces represent values of zero. The dashed horizontal lines represent the thresholds for defining learning biases; participants whose absolute value of the bias score on the first block was $< 25\%$ were defined as “balanced learners” (gray areas). Stable learners are those who had similar bias on the first and last blocks; three stable learners are labeled as examples: (1) is reward biased on both the first and last blocks; (2) is punishment biased on both blocks, and (3) is a balanced learner on both blocks. Approximately, 70% and 55% of participants in both BI groups were balanced and stable, respectively (Pearson chi-square, both $p > 0.8$).

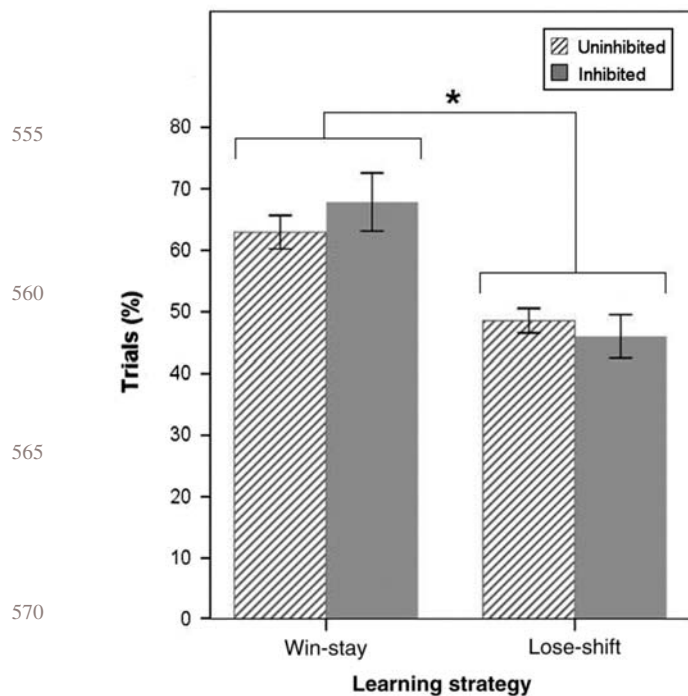


Figure 4. Percent of trials during the first block of Experiment 1 in which participants showed “win-stay” and “lose-shift” behaviors in inhibited ($n = 22$) versus uninhibited ($n = 52$) participants. In general, participants showed a higher percentage of win-stay than lose-shift trials (rmANOVA, $p < 0.001$). However, inhibited participants did not differ from their uninhibited counterparts. Asterisks indicate significant differences ($p < 0.05$). Error bars indicate SEM.

[$F(1,42) = 34.38$, $p < 0.001$], with participants skipping more punishment than reward trials. There was an interaction between trial block and feedback type [$F(3,126) = 21.80$, $p < 0.001$]. *Post hoc* tests revealed a significant effect of block only in the punishment trials [$F(3,129) = 20.06$, $p < 0.001$], possibly due to a floor effect (minimal skipping) in the reward trials. Although six participants skipped $\geq 20\%$ of punishment trials on the very first block of training, none of these participants skipped $> 5\%$ of the reward trials on this block.

Figure 7 shows percent optimal classification responses on all reward and punishment trials that were not skipped, in participants categorized as skippers versus non-skippers. Eleven participants (13.9%) were not included in the following analysis, as these participants skipped all the trials on at least one block, and thus did not have classification data that could be analyzed on that block. There were no significant differences in gender or age between those 11 participants and the remaining 33 skippers (both $p > 0.20$). However, this group had significantly higher BI scores [$t(42) = 2.753$, $p = 0.009$], which is consistent with the finding that inhibited participants showed more skipping responses. Among the remaining 68 participants, there were main effects of BI [rmANOVA, $F(1,64) = 6.839$, $p = 0.011$] and trial

block [$F(3,192) = 7.023$, $p < 0.001$] on optimal classification performance, showing that although both groups improved performance across blocks, classification performance was better in uninhibited participants. There was also an interaction between trial block and feedback type [$F(3,192) = 8.527$, $p < 0.001$], and an interaction between trial block, feedback type and skipping [$F(3,192) = 5.241$, $p = 0.002$]. *Post hoc* tests revealed that among skippers (Figure 7C,D), classification performance on reward trials was better than on punishment trials on the last block [$t(35) = 3.336$, $p = 0.002$]; this difference did not occur in non-skippers (Figure 7A,B). Total correct responding was also higher in uninhibited than in inhibited participants [$F(1,77) = 15.134$, $p < 0.001$]. Specifically, uninhibited participants received less punishments [$t(47.5) = 2.801$, $p = 0.007$], and more rewards [$t(77) = 2.139$, $p = 0.036$]. There were no other main effects or interactions.

The finding of better classification performance in uninhibited participants in Experiment 2 contrasted with the results of Experiment 1, where inhibited participants showed better classification performance.

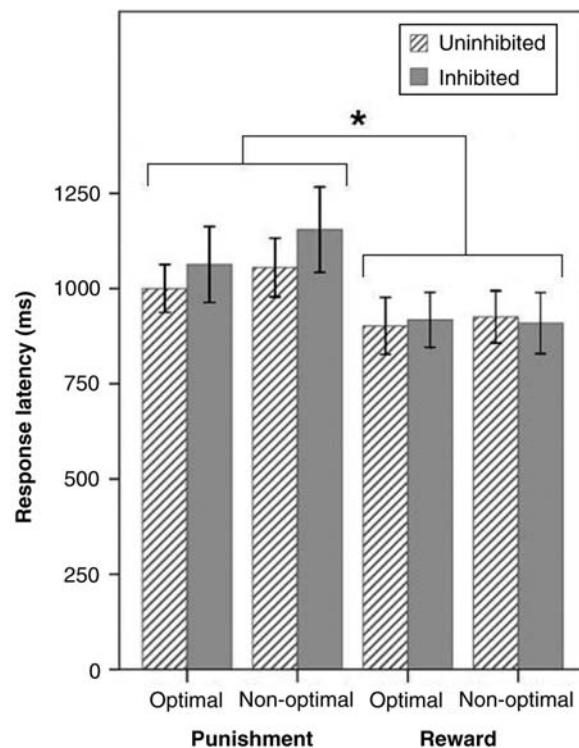


Figure 5. Mean response latency (ms) in Experiment 1, as a function of feedback type (reward vs. punishment) and participant's response (optimal vs. non-optimal) in inhibited ($n = 21$) versus uninhibited ($n = 51$) participants. While responses on punishment trials were generally slower than responses on reward trials (rmANOVA, $p < 0.001$), there was no significant difference in latency between optimal or non-optimal responses ($p = 0.067$) or between inhibited participants and their uninhibited counterparts ($p = 0.73$). Asterisks indicate significant differences ($p < 0.05$). Error bars indicate SEM.

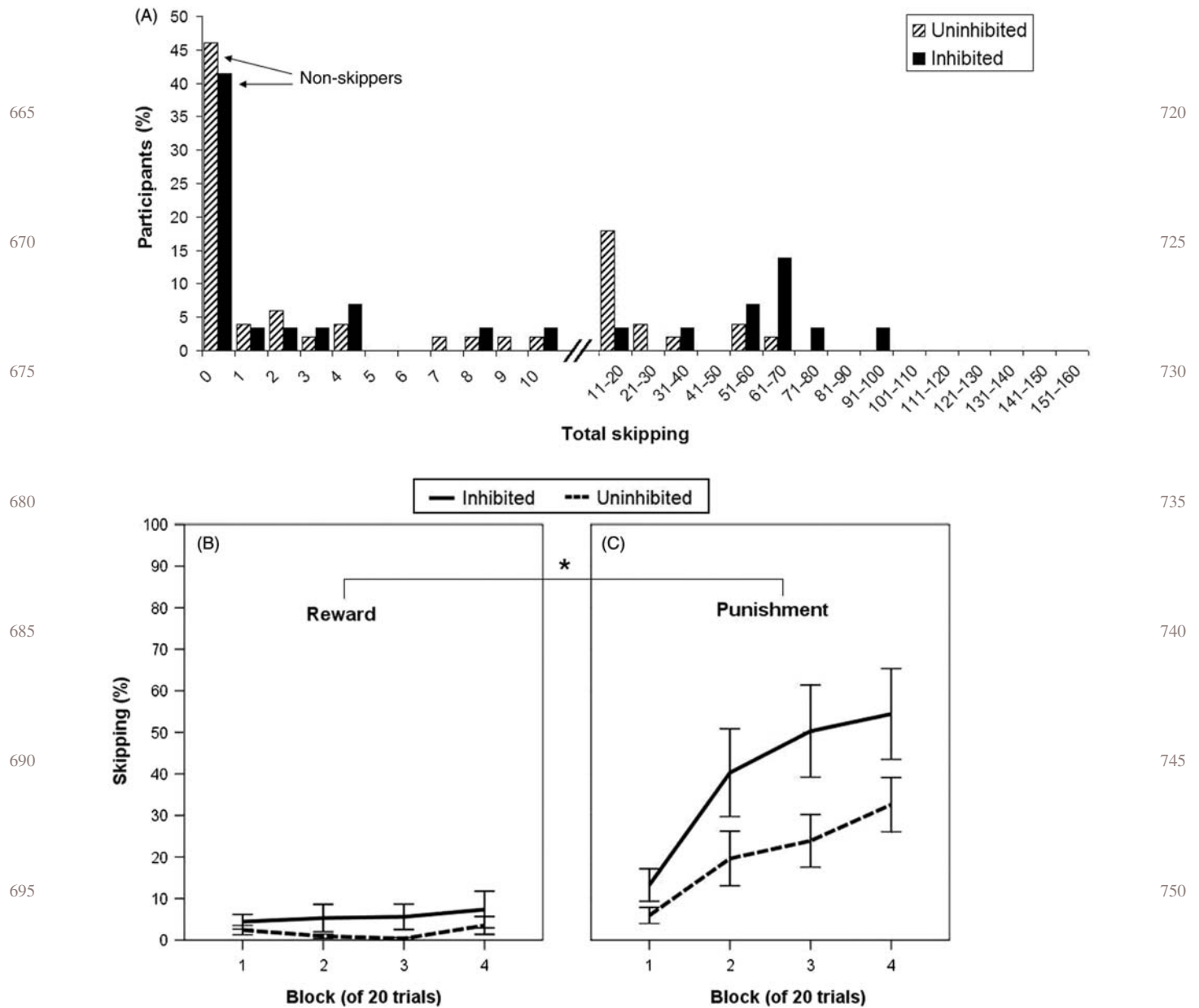


Figure 6. Skipping behavior in Experiment 2. (A) Distribution of skipping frequency in inhibited ($n = 29$) and uninhibited ($n = 50$) participants. Nearly, half of the participants made no skipping responses. (B, C) Mean percent reward and punishment trials skipped per block, among participants who made at least one opt-out response. Participants showed increased numbers of opt-out responses across blocks (rmANOVA, $p < 0.001$), with more skipping on punishment than on reward trials ($p < 0.001$) and more skipping performed by inhibited than uninhibited participants ($p = 0.02$). Asterisks indicate significant differences ($p < 0.05$). Error bars indicate SEM.

Further, on punishment trials in Experiment 2, frequency of opt-out responses was negatively correlated with optimal classification performance ($r = -0.352, p = 0.019$). As skipping of punishment trials can be considered an adaptive response, because it eliminates the risk of punishment on that trial, we repeated the previous ANOVA analysis on “adaptive responses,” counting either skipping responses or optimal classification responses for punishment trials (Figure 7B,E), but only optimal classification responses for reward trials (Figure 7A,C). Now, data from all 79 participants could be included. Most

importantly, in contrast to the previous analysis, this time no main effect of BI was found ($p = 0.196$). Other main effects of trial block [$F(3,225) = 21.178, p < 0.001$], feedback type [$F(1,75) = 5.645, p = 0.020$] and skipping [$F(1,75) = 6.898, p = 0.010$] were observed, as was the interaction between trial block and skipping [$F(3,225) = 4.656, p = 0.004$]. The interaction between trial block and feedback type approached significance [$F(3,225) = 2.579, p = 0.054$]. *Post hoc t*-tests revealed that the difference between skippers and non-skippers was significant only on the last block [$t(77) = 3.105, p = 0.003$].

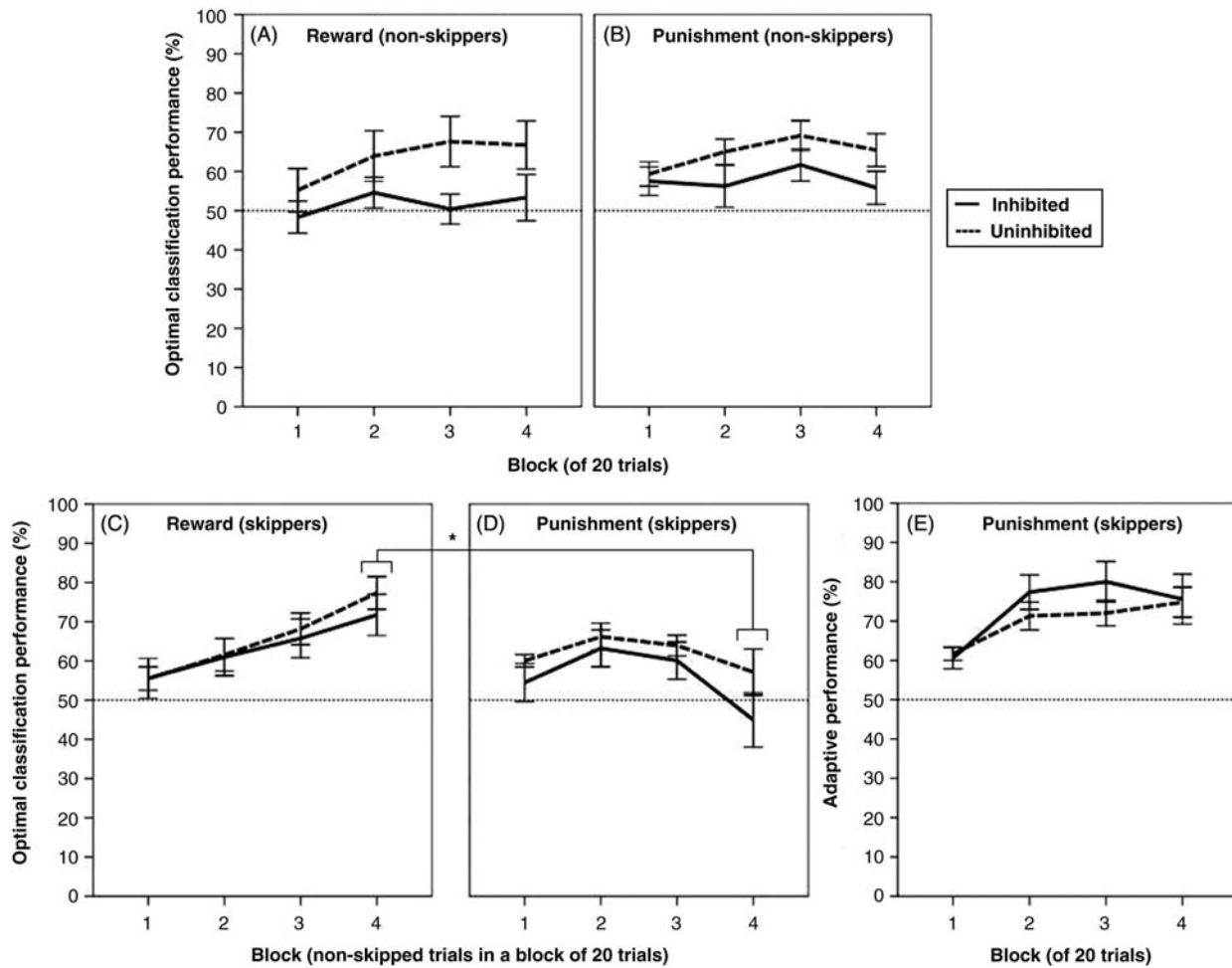


Figure 7. Percent optimal classification responses in Experiment 2 (on trials where a classification response was made), among “non-skippers” ($n = 35$) on (A) reward and (B) punishment trials, and among “skippers” ($n = 44$) on (C) reward and (D) punishment trials. (E) Adaptive responding on punishment trials (including both optimal classification and skipping response) by skippers. The significant difference observed between BI groups in figures A–D (rmANOVA, $p < 0.011$) is eliminated when skipping is scored as an adaptive response (E; $p = 0.20$). Dotted horizontal line represents chance performance (50%). Asterisks indicate significant differences ($p < 0.05$). Error bars indicate SEM.

Figure 8 depicts the mean latency on trials where a classification response was made. As in Experiment 1, one inhibited participant and one uninhibited participant were excluded as they did not have any non-optimal reward trials that could be analyzed. Overall, there were longer latencies in skippers than in non-skippers [rmANOVA, $F(1,73) = 5.111$, $p = 0.027$], on punishment than on reward trials [$F(1,73) = 21.02$, $p < 0.001$], and in participants choosing the non-optimal versus optimal response [$F(1,73) = 8.597$, $p = 0.004$]. Although no main effect of BI was found ($p = 0.91$), there were interactions between BI and skipping [$F(1,73) = 7.915$, $p = 0.006$], as well as between feedback type and skipping [$F(1,73) = 5.903$, $p = 0.018$] and between performance and feedback type [$F(1,73) = 7.803$, $p = 0.007$]. To further investigate the BI \times skipping interaction, *post hoc* tests

revealed that inhibited skippers responded significantly more slowly than inhibited non-skippers [$t(26) = 2.565$, $p = 0.016$], while the uninhibited participants did not show any difference between skippers and non-skippers ($p = 0.59$).

Lastly, as in Experiment 1, additional analyses were carried out to verify that other potential differences between participants did not account for the different performances observed between BI groups. Learning bias and bias stability did not differ between inhibited and uninhibited participants or between skippers and non-skippers; all four groups had approximately 77% participants who were balanced learners (both $p > 0.70$) and 44.4–63.6% who were stable learners (both $p > 0.20$). Moreover, win-stay and lose-shift behavior strategies were not different between inhibited and uninhibited groups or between skippers and non-skippers (both $p > 0.80$).

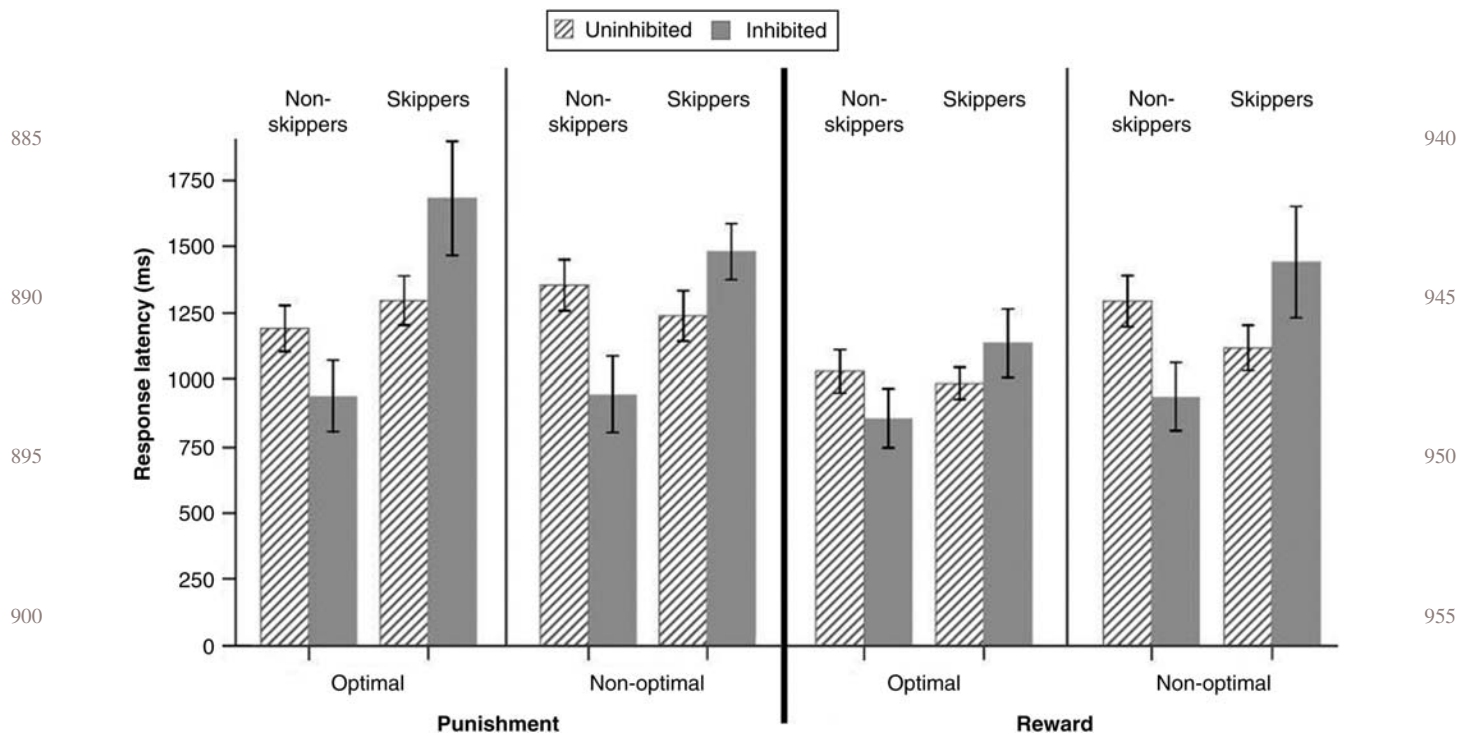


Figure 8. Mean response latency (ms) in Experiment 2 for trials on which a classification response was made, as a function of feedback type (reward vs. punishment), participant's response (optimal vs. non-optimal) and skipping (skippers vs. non-skippers) in inhibited vs. uninhibited participants. Across response and feedback types, inhibited skippers ($n = 16$) responded significantly more slowly than inhibited non-skippers ($n = 12$; $rmANOVA, p = 0.016$), while the uninhibited skippers ($n = 27$) did not differ from uninhibited non-skippers ($n = 22$; $p = 0.59$). Error bars indicate SEM.

Discussion

The aim of this study was to better understand the relation between BI, a temperamental trait conferring vulnerability to anxiety disorders, and the acquisition and expression of avoidance behavior, a predominant symptom in anxiety disorders. We considered two types of avoidance: learning optimal classification responses that minimized risk of punishment and “opt-out” responding that allowed the participant to eliminate any risk of punishment. Previously, BI was linked to faster acquisition of a classically conditioned eyeblink response (Myers et al. 2012b); in Experiment 1, inhibited participants showed facilitated classification learning to on-screen feedback in the form of verbal statements (“Correct”/“Incorrect”) and point gain or loss, which did not translate into money or any primary reinforcer or punisher. In contrast, a recent study which used the same task (Bódi et al. 2009) showed that harm avoidance is specifically associated with enhanced performance on punishment trials; this highlights a potential difference between BI and the related trait harm avoidance, which was proposed to be indicative of BI (Cloninger 1987).

In Experiment 2, we tested participants' tendency to withdraw or “opt out” of responding, when this option is available. Although many prior studies have

examined forced choice behavior on classification and related tasks (Frank et al. 2004; Bódi et al. 2009), to our knowledge, this experiment is the first in which participants are given the option to opt out of trials. Unexpectedly, almost half of the participants in Experiment 2 never took advantage of the opt-out response; none of the variables we investigated appeared to differentiate those who made the response at least once (“skippers”) versus those who did not (“non-skippers”). Nevertheless, as hypothesized, inhibited participants opted out significantly more than their uninhibited peers. Figure 6B,C showed that skipping was generally selective for punishment trials, and tended to increase across trials, rather than present as a pre-existing tendency. Indeed, skipping was a negatively reinforced response, in which the removal of risk of punishment resulted in an increase in frequency of the response (also termed omission training).

However, the main conclusion from Experiment 2 is that both inhibited and uninhibited individuals may achieve comparable performance on the task, indexed as adaptive responding, but they may preferentially use different strategies. Specifically, while uninhibited individuals learn to make classification responses to minimize probability of punishment, inhibited individuals are more likely to skip punishment trials

altogether. Although this latter strategy results in fewer overall punishments obtained, it may be that in real-world situations, a tendency to rely on such “opting-out” behavior may confer vulnerability for the development of pathological avoidance.

In both experiments, we ruled out several other aspects of behavior that could account for the differences between BI groups, including learning bias, learning strategy and latency. Our finding that the majority of participants showed balanced learning is consistent with previous work on a related probabilistic selection task (Simon et al. 2010), although that experiment did not consider BI. The finding that participants showed greater win-stay than lose-shift behavior is also consistent with previous literature (Frank and Kong 2008; Simon et al. 2010). Lastly, in Experiment 2, an unexpected and intriguing latency difference emerged: inhibited skippers responded more slowly than inhibited non-skippers. Longer latencies might reflect conflict that some inhibited individuals experience when determining how to respond to a potential threat.

Besides these core issues, this study is one in a small but growing literature to use the AMBI questionnaire as a self-report measure for current (adult) BI and to show relationships between AMBI scores and behavior (Holloway and Servatius 2010; Caulfield et al. 2011; Myers et al. 2012a,b). In both experiments, AMBI scores were similar, with about one-third of participants classified as inhibited. Future research might consider whether other instruments assessing BI (such as the widely adopted BIS/BAS scale; Carver and White 1994) would show similar associations.

This study has several limitations that could be addressed in future work. First, it would be beneficial to consider a richer set of demographic variables such as ethnicity, marital status, history of psychiatric illness, brain injury and substance use/abuse. Second, larger samples might allow investigating skipping as a continuous variable, rather than classifying participants as skippers versus non-skippers. Furthermore, it is unclear why only about half of the participants used the skipping option in Experiment 2. Motivation or demand characteristics might have been involved, such that participants saw little value in skipping or felt this would be considered “cheating.” It is possible that by adding a monetary reinforcement, more participants would be motivated to opt out of punishment trials. Finally, the negative correlation between optimal performance and skipping on punishment trials in Experiment 2 should be further investigated. Currently, it is unclear whether high rates of skipping impair learning, by reducing opportunities for feedback, or poor learning produces high rates of skipping, as participants who do not learn the optimal classification on specific stimuli may begin skipping trials with those stimuli. One way to explore this issue in future might be by providing feedback regarding the

optimal classification response on skipped trials, so that skipping does not entail reduced feedback.

Moreover, uncertainty is an important attribute of a probabilistic classification task, because it is impossible to perfectly predict the correct response on every trial. Individuals who have high intolerance to uncertainty are also at higher risk for anxiety disorders (Buhr and Dugas 2002), and it is possible that BI and intolerance of uncertainty are related constructs. It would be interesting to test individuals on a version of the task that reduces ambiguity: either a deterministic version of the task where each stimulus is 100% predictive of category membership, as opposed to 80% in the current task, or one that eliminates the no-feedback outcome (after skipping a response, or after classification that results in failure to obtain reward or successful avoidance of punishment). In such future studies, it may also be of interest to directly assess both BI and uncertainty of tolerance as personality constructs, to better understand their presumed relation and mutual involvement in human behavior patterns. Finally, a prior study has also associated performance on this probabilistic classification task (“Forced-Choice” version) and the midbrain dopaminergic system (Bódi et al. 2009). Given the prior literature linking BI with brain substrates including cerebellum, amygdala and hippocampus (Blackford et al. 2009, 2012), an interesting direction for future work would be to explore brain activation in inhibited versus uninhibited individuals on this task.

In conclusion, this work explored relationships between performance on a computer-based task and personality characteristics, specifically, trait BI. The main reason for studying behavior patterns in inhibited individuals is that BI confers increased risk for anxiety disorders, which entail pathologically exaggerated avoidance as a predominant symptom. This work suggests that BI is associated with enhanced associative learning, which leads us to hypothesize that the exaggerated avoidance in anxious individuals may be a by-product of facilitated associative learning rather than a stand-alone symptom. Our current findings indicate that higher tendency to avoid is a pre-existing behavior pattern that can be observed in healthy young adults. As such, it might precede the development of an anxiety disorder (and potentially contribute to its etiology and pathogenesis). Longitudinal studies would be required to determine whether non-anxious individuals who do show accelerated learning and/or high tendency to opt out on this task do indeed show higher long-term risk for the development of anxiety disorders. Such results have implications for understanding the transition from temperamental vulnerabilities to symptomatic behaviors seen in anxiety disorders, and potentially, might assist with designing better therapeutic strategies to help anxious individuals.

Declaration of interest: This work was supported by the NSF/NIH Collaborative Research in Computational Neuroscience (CRCNS) Program, by NIAAA (R01 AA018737) and by additional support from the SMBI. The authors report no conflicts of interest. The authors alone are responsible for the content and writing of the paper.

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