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Unbending mind: Individuals with hoarding disorder do not modify decision strategy in response to feedback under risk

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ABSTRACT

Cognitive-behavioral models of hoarding disorder emphasize impairments in information processing and decision making in the genesis of hoarding symptomology. We propose and test the novel hypothesis that individuals with hoarding are maladaptively biased towards a deliberative decision style. While deliberative strategies are often considered normative, they are not always adaptable to the limitations imposed by many real-world decision contexts. We examined decision-making patterns in 19 individuals with hoarding and 19 healthy controls, using a behavioral task that quantifies selection of decision strategies in a novel environment with known probabilities (risk) in response to feedback. Consistent with prior literature, we found that healthy individuals tend to explore different decision strategies in the beginning of the experiment, but later, in response to feedback, they shift towards a compound strategy that balances expected values and risks. In contrast, individuals with hoarding follow a simple, deliberative, risk-neutral, value-based strategy from the beginning to the end of the task, irrespective of the feedback. This seemingly rational approach was not *ecologically rational*: individuals with hoarding and healthy individuals earned about the same amount of money, but it took individuals with hoarding a lot longer to do it: additional cognitive costs did not lead to additional benefits.

1. Introduction

Hoarding disorder (HD) is characterized by severe and persistent difficulty discarding or parting with possessions, leading to clutter that precludes normal use of living spaces (APA, 2013). Existing cognitive-behavioral therapies have limited efficacy, and underlying neurocognitive impairments are not well understood (Tolin, 2011). It has been suggested that improving underlying cognitive deficiencies may significantly enhance efficacy of treatments (Hacker et al., 2016).

Current cognitive-behavioral models of HD propose that the hallmark criterion of HD, difficulty discarding, results in part from impairments in information processing (Frost and Hartl, 1996), decision making (Frost and Gross, 1993; Frost and Shows, 1993; Samuels et al., 2002; Steketee and Frost, 2003), and inattentiveness (Hacker et al., 2016; Tolin and Villavicencio, 2011). Indeed, decision-making problems and problems with attention have been observed in hoarding samples, on self-report measures (Frost and Gross, 1993; Frost and Shows, 1993; Steketee and Frost, 2003) and in real world situations (Frost and Gross, 1993).

Laboratory tests of decision making in individuals with HD, on the other hand, have yielded mixed findings. For instance, using the Wisconsin card sorting task (WCST; Grant and Berg, 1948), some studies found that individuals with HD may have *difficulty incorporating feedback into their decision making* (McMillan et al., 2013; Pedron et al., 2015), while others (Tolin et al., 2011) found no difference between individuals with HD and controls. Studies of decision making under uncertainty in HD that used self-report measures of uncertainty intolerance (Freeston et al., 1994) found that individuals with HD are more uncertainty averse than healthy individuals (Oglesby et al., 2013; Wheaton et al., 2016). In contrast, in a recent study (Pushkarskaya et al., 2017), we found no difference in behavior-based measures of uncertainty aversion between individuals with HD and controls. Other commonly used behavioral tests of executive function (Tower of London, Set Shifting tasks, Iowa Gambling task, Probabilistic Learning and Reversal task) have similarly produced mixed results (Dozier et al., 2016; Grisham et al., 2010; Mackin et al., 2015; McMillan et al., 2013;

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Morein-Zamir et al., 2014; Pedron et al., 2015; Sumner et al., 2015; Tolin et al., 2011).

Few studies have explicitly probed abnormalities in information processing in hoarding disorder. The most robust finding is that individuals with HD exhibit slow processing (Frost and Hartl, 1996; Mackin et al., 2011). Here we aim to add to this line of research by employing a theoretical dual processing framework (Kahneman, 2011; Petty et al., 2005) and well-validated tools of behavioral economics, detailed below.

Decisions involving a choice between alternatives can often be effectively made using step-by-step deliberation, following clear rules of value-based decision making (Rangel et al., 2008). During deliberative decision making, some subjective measure of importance (i.e. value) is assigned to each alternative, and then the option with the highest value is selected. Deliberative processing is 'rational' and can often lead to outcomes that are considered normatively correct (e.g. maximized subjective value). However, deliberative processing is generally slow and not adaptable to limitations of decision contexts (Kahneman, 2011; Kuo et al., 2009). In some contexts, using deliberative processing inappropriately may lead to significantly longer decision times without significant improvement in decision quality (Czerlinski et al., 1999; Gigerenzer and Goldstein, 1996; Goldstein and Gigerenzer, 2002). Deliberative processing also demands more information; inadequate information under conditions of uncertainty may, in extreme cases, result in inability to make a choice.

Alternatively, choices may be made using intuitive judgments that are derived from an "informal and unstructured mode of reasoning" (Kahneman et al., 1982). Intuitive judgments have been often interpreted as "irrationalities" in decision making (Kahneman, 2011; Kahneman and Tversky, 1979; Tversky and Kahneman, 1973). However, relying on intuitive judgements, rather than a normative rule, may be advantageous in many decision contexts, when time, information, or cognitive resources are limited. The concept of "ecological rationality" (Goldstein and Gigerenzer, 2002) suggests that, in complex real world scenarios, individuals select an appropriate tool from the available set of decision-making strategies in response to contextual demands. Available tools include both a deliberative strategy and a collection of fast and frugal intuitive judgments. Ecological rationality leads to at least "good enough" choices, and avoids "getting stuck" when the information or time necessary for deliberative reasoning is not available.

Individuals with HD exhibit slow information processing (Frost and Hartl, 1996; Mackin et al., 2011) and demonstrate profound indecisiveness in real world situations (Frost and Gross, 1993). Thus, we hypothesize that individuals with HD have a bias towards unambiguous normative rules and deliberative processing, at the expense of ecological rationality in complex decision environments.

Our hypothesis can be tested in a laboratory setting using the Gambling Task (Camille et al., 2004; Coricelli et al., 2005). This task requires participants to make 40 sequential choices between gambles with fully specified probabilities and outcomes; in the partial feedback condition, participants are told the outcome of their choice after each trial.[1] This feedback does not provide any new information about the decision context, since probabilities and potential outcomes are already clearly specified. It does, however, provide clear feedback as to the effectiveness of current decision strategies, which may motivate decision makers to adjust them. Strategies can be simple (e.g. based only on expected values of the alternatives) or compound (e.g. balancing values and risks).

Choice data can be used to infer the evolution of strategy selection during the task. Prior studies (Brand, 2008; Brand et al., 2009; Shanks et al., 2002) have demonstrated that in this task, healthy individuals tend to follow intuitive strategies and explore early in the task, but later they tend to shift toward a "normatively correct" value-based decision strategy. This effect has been shown to be stronger for individuals with a general bias toward intuitive judgments; individuals who adopt a clear deliberative rule from the beginning are largely unaffected by feedback in this decision contexts (Brand et al., 2009; Schiebener and Brand, 2015). Consequently, we expected that performance of individuals with HD on the Gambling Task would be different from that of healthy individuals: they would follow clear rules of value-based decision making from the beginning of the task, irrespective of feedback, eschewing the exploration of intuitive strategies seen in controls.

2. Methods

2.1. Participants

All procedures were approved by the Yale University Human Investigation Committee and the Hartford Hospital Institutional Review Board. All participants provided written informed consent and completed a demographic questionnaire (SM S1); IQ of all participants was estimated using the Kaufman Brief Intelligence Test (Kaufman, 1979). They were compensated for their time, as detailed below.

Nineteen individuals with a HD diagnosis and with no OCD diagnosis, unmedicated for at least 8 weeks, were recruited through the Anxiety Disorders Center at the Institute of Living, Hartford Hospital. Diagnoses were established by doctoral-level clinicians and confirmed using a structured diagnostic interview for DSM-5 anxiety, mood, and obsessive-compulsive and related disorders (DIAMOND; Tolin et al., 2016). Severity of hoarding symptoms was assessed using the Saving Inventory – Revised (SI-R; Frost et al., 2004).

Nineteen healthy participants (Healthy Control, HC) were recruited in the New Haven, CT area using flyers. Controls matched our clinical sample on age, gender, IQ, income, and education (Table 1).

2.2. Task

Participants were asked to make 40 consecutive choices between two gambles with precisely specified potential outcomes and probabilities associated with them, with no time limit (Fig. 1). Gambles included potential gains of $5 or $20 and/or potential losses of -$5 and -$20 (see SM S2 for the full list of lotteries). After a gamble was selected, the arrow corresponding to this gamble rotated for 20 s, and then the outcome was revealed. Next, to promote feedback evaluation, the participant was asked to rate how he/she felt about the realized outcome, on a sliding scale from "Extremely unhappy" to "Extremely happy." Points earned/lost on each trial were added up and exchanged for dollars at the end of the game, at the rate 5 points for $1. Task earnings were added to a participation fee of $10.

Importantly, the outcome of each gamble was predetermined, even though participants were told that the outcomes were random. Thus, it can be objectively determined which group's strategies were more advantageous, by comparing the total points earned. In other words, the task allows direct comparison of *ecological* effectiveness of decision strategies across participants.

2.3. Data analysis

Statistical analyses were performed using SPSS v.21 and NLogit v4.0.

2.3.1. Affective responses

Ratings of affective responses were analyzed using 4 × 1 repeated measures ANOVA with a within subject factor (realized outcome: -$20, -$5, $5, $20), and a between subject factor (HD diagnosis). Since we hypothesized that individuals with HD are less affected by feedback, we predicted that their affective responses would be less influenced by

[1] In the complete feedback condition of the Gambling Task, the participants also receive information about the outcome of the option that they did not choose. However, this condition is not relevant to our hypothesis here and was not used in the current study.

Table 1
Group Demographics.

	Patients, N = 19	Controls, N = 19	p-value
AGE	53.7 ± 1.26	49.2 ± 1.9	*0.06*
Male	0.47 ± 0.12	0.47 ± 0.12	*1.00*
IQ	112.4 ± 4.00	105.8 ± 3.53	*0.23*
Income	3.1 ± 0.53	4.4 ± 0.56	*0.08*
Education	4.8 ± 0.16	5.2 ± 0.23	*0.25*
Saving Inventory -revised (SI-R)			
Total SI-R scale	56.35 ± 3.7	9.29 ± 2.0	*< 0.001*
Clutter subscale	23.41 ± 1.7	2.29 ± 0.7	*< 0.001*
Difficulty Discarding subscale	18.41 ± 1.3	3.12 ± 0.8	*< 0.001*
Excessive Acquisition subscale	14.53 ± 1.5	3.88 ± 0.8	*< 0.001*

Note: Significance of the between-group difference, p-value, for Age, IQ, Income, Education, and SI-R scores is based on the one-way ANOVA; significance of the between -group difference, p-value, for Male is based on the Pearson's chi-squared test ($\chi2$).

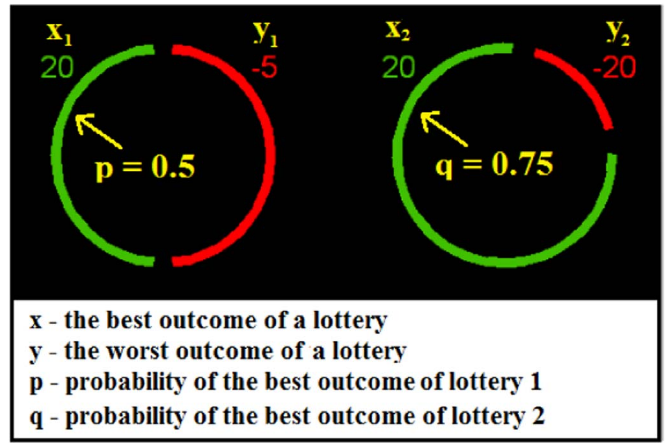

Fig. 2. Value-based model notation.

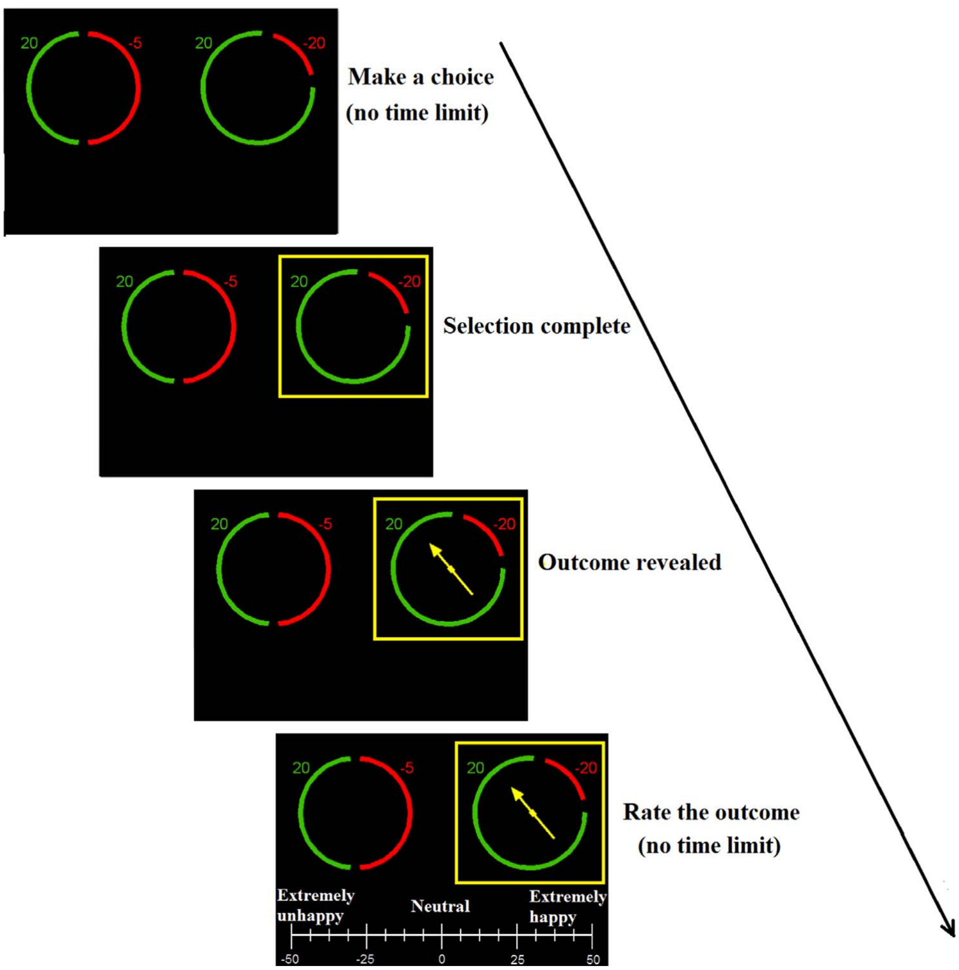

Fig. 1. Trial structure of the behavioral task.

realized outcomes than those of healthy controls.

2.3.2. Decision strategies

2.3.2.1. Model. Fig. 2 summarizes the key notation of the model: $x1$ and $y1$ denote the two possible outcomes of gamble 1 ($G1$), with $x1>y1$. Similarly, $x2$ and $y2$ denote the two possible outcomes of gamble 2 ($G2$), with $x2>y2$. The respective probabilities of outcomes $x1$ and $y1$ are p and $1-p$; the respective probabilities of outcomes $x2$ and $y2$ are q and $1-q$. Using this notation, we introduce three decision strategies that may affect a choice of gamble 1 over gamble 2: expected value maximization, risk minimization, and loss minimization.

The *expected value* of gamble 1 ($EV1$) is equal to $[p*x1 + (1-p)*y1]$, and the expected value of gamble 2 ($EV2$) is equal to $[q*x2 + (1-q)*y2]$. A decision-maker motivated by expected value should choose gamble 1 if the expected value of gamble 1 is greater than that of gamble 2 – or, equivalently, if

$$v = [p \times x_1 + (1-p) \times y_1] - [q \times x_2 + (1-q) \times y_2] \quad (1)$$

is positive.

The *Risk* that a decision-maker faces in choosing gamble 1 is defined as variation in value across potential outcomes of gamble 1 (Coricelli et al., 2005; Gillan et al., 2014) and is equal to $q\times(x_1 - EV_1)^2+(1 - q)\times(y_1 - EV_1)^2$; the risk for gamble 2 is equal to $p\times(x_2 - EV_2)^2+(1 - p)\times(y_2 - EV_2)^2$. A risk minimizing decision-maker chooses gamble 1 if

$$r = [q \times (x_2 - EV_2)^2 + (1-q) \times (y_2 - EV_2)^2] - [p \times (x_1 - EV_1)^2+(1-p)\times(y_1 - EV_1)^2] \quad (2)$$

is positive.

Finally, if a decision maker aims to minimize potential losses, then gamble 1 is preferable if the measure *l:*

$$l = y_1 - y_2, \quad (3)$$

is positive.

The probability of choosing gamble 1 ($Prob(G1_{it})$), where t denotes trial and i denotes individual, is calculated using:

$$P(G1_{it}) = 1-P(G2_{it}) = F(v_{it}, r_{it}, l_{it}), \quad (4)$$

where F is the inverse logit function, $F(\theta)=e^{\theta}/(1+e^{\theta})$, and θ is a linear function of v, r, and l. Note that the three decision strategies– expected value maximization, risk minimization, and loss minimization – are not mutually exclusive; choices can be affected by several considerations simultaneously (for more details see SM S2). Also note that value maximization is typically considered as a 'normatively correct' strategy (von Neumann and Morgenstern, 1944), while loss minimization entails the simplest calculations.

2.3.2.2. Search for a change of strategy point. We hypothesized that HC would rely on more intuitive and exploratory strategies in the beginning of the experiment, and then switch to more deliberative value-based decision making. This can be tested by employing a segmentation of time series approach (Chu, 1995; Keogh et al., 2004), detailed in the Supplementary materials (SM S3). Briefly, segmentation consists of two interdependent steps: detecting nonstationarity and localizing change points. Detecting nonstationarity involves testing whether the same model can describe data throughout the time series. We fit choice data to the logit model (Eq. (4)) using panel data with random effects analysis in a sequence of growing intervals. We use a small reference window, and then extend it to the whole time series by adding one time point at a time. The minimum sample required to test our logit model (Eq. (4)) is 117 observations (Cohen, 1988); thus for the panel data from 19 individuals we need at least 7 periods in a reference window. Because we hypothesized that choices of HC would converge to value-based choices by the end of the experiment, we use the last 7 trials as a reference window. Next, we generate 33 growing test windows by adding one period at a time to the last 7 trials; we fit our logit model to these test windows sequentially. For each interval, we evaluate the goodness of model fit using the Hosmer-Lemeshow X^2. An acceptable model fit ($p > 0.05$) indicates that participants' choices can be explained by their sensitivity to expected value, risk, and anticipated loss; poor model fit suggests that our model does not capture decision strategies of our participants and implies nonstationarity.

In the case of nonstationarity, a change of strategy point is localized by identifying at what time period the change in model parameters occurs (SM S3.2). This is done by comparing parameter estimates from a series of reference and test windows. We use the last 7 trials (trials 34–40) as the first reference window; the corresponding test window consists of the previous 7 trials (trials 27–33). Next, we generate 27 growing test windows by adding one period at a time to the last 7 trials; a corresponding test window always consists of the previous 7 trials. We fit our logit model to these reference windows and corresponding test windows sequentially. If the parameter estimates from the k^{th} test window are sufficiently different from the parameters from the k^{th} reference window, it may reflect a change in strategy. If t trial is identified as a change in strategy point, then we term the interval $[t + 1, T]$ the *steady state* interval and the interval $[1, t]$ the *initial trials* interval.

2.3.3. Overall performance on the task: cost-benefit analysis

To assess whether any difference in strategy selection between HD and HC is ecologically effective, we compared costs (decision time) and benefits (points earned) across two groups. For each participant we calculated the average of log-transformed response time (van der Linden, 2006). We expected that response time for individuals with HD would be longer than for HC, reflecting higher cognitive costs for HD. For each participant we also calculated the total of points earned. We expected that on a group level, individuals with HD would not earn more points than HC, reflecting ecological ineffectiveness of strategies employed by HD.

3. Results

3.1. Affective responses

A 2 × 4 repeated measures ANOVA with affective ratings as the dependent variable, realized payoff (-$20, -$5, $5, $20) as a within-subject factor, and diagnosis (HD vs. HC) as a between-subjects factor revealed a significant main effect of realized payoffs ($F(3,35) = 257.4$, $p < 0.001$) and a significant interaction between realized payoff and diagnosis ($F(3,35) = 5.49$, $p = 0.002$). Consistent with our expectations, affective responses of HD were less influenced by realized outcomes than those of HC: HD were not as happy with wins and not as unhappy about losses (Fig. 3).

3.2. Decision strategies

3.2.1. Change of strategy point

Detailed presentation of the results of a search for a change of strategy point is given in Supplementary materials SM S.3. For healthy individuals, data from the initial 10 trials do not fit our logit model well (Fig. 4**A**), suggesting nonstationarity. Further analyses revealed a clear change in strategy point for HC: parameter estimates from the test window that included trials 15–40 were significantly different from the parameters from the corresponding test window that included trials 8–14 ($p < 0.03$, SM S3**,** Table S3.2**a**). Thus, we consider the trials 1–14 an initial exploratory period, and trials 15–40 a steady state period. These results are consistent with our expectation that healthy individuals tend to explore in the beginning of the task, and converge to a clear strategy later in the experiment. Since HC appear to employ

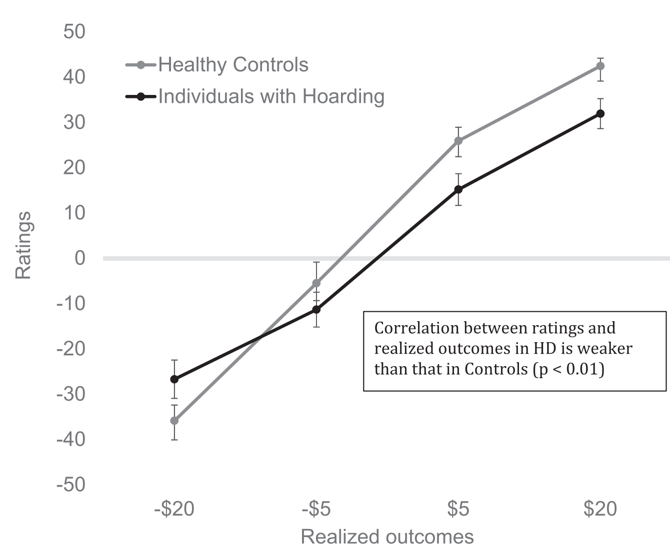

Fig. 3. Ratings of realized outcomes across groups.

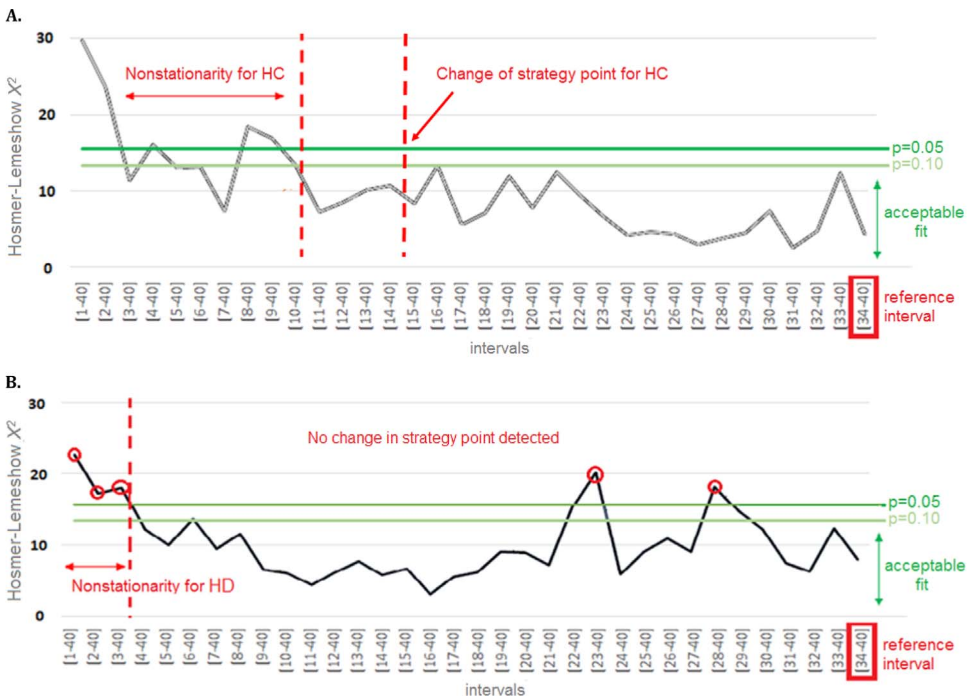

Fig. 4. Growing Sliding Window test for stability of the logistic model using panel data with random effects analysis for healthy control (**A**) and individuals with hoarding disorder (**B**), detailed in Supplementary materials SM S3. For search for a change in strategy point also see Supplementary materials SM S3.

different strategies during first 14 trials and remaining 26 trials, we fit our logit model (Eq. (4)) to these two intervals separately.

The search for a change point in individuals with HD produced very different results (Fig. 4**B**). Model fit was unacceptable only for intervals that included trials 1–3 (Hosmer-Lemeshow $p < 0.05$). No change of strategy point was detected (SM S4), which suggest that individuals with HD followed the same strategy throughout the experiment, which is consistent with our expectations.

3.2.2. Initial and steady state strategies

We tested for group differences in the degree to which expected value maximization, risk minimization, and loss minimization motivated choice behavior, both during the initial trials (trials 1–14) and the steady-state trials (trials 15–40).

In the beginning of the experiment, consistent with our expectations, HC appeared on average to be insensitive to expected value, and exhibited loss avoidance and risk seeking, consistent with exploratory and intuitive decision making (Table 2, Fig. 5; recall that loss avoidance is the easiest strategy and involves the simplest computations). Since during these initial trials choices of HC were not well explained by our logit model (Hosmer-Lemeshow $p < 0.05$) the magnitude of these parameter estimates should be treated with caution. Later in the task, consistent with our expectations, HC shifted to value-based strategies (i.e. they become sensitive to expected value in the logit model) and became risk-averse (Table 3, Fig. 5).

In contrast, and consistent with our expectations, HD were motivated by maximization of expected value throughout the experiment (Tables 2 and 3, Fig. 5). In contrast to HC, during the steady state (trials 15–40), they showed no significant risk aversion.

3.3. Overall performance: costs versus benefits

3.3.1. Group differences

Our data indicate that HC changed choice strategies over the course of the experiment, while HD were consistent throughout. We also find that HD followed a normative value-based strategy; in contrast, HC appeared to explore during the early trials, and only then to switch to value-based and risk averse choices. We conducted a cost-benefit analysis to evaluate whether the seemingly rational approach employed by individuals with HD was indeed beneficial in this decision context.

Response time of HCs (Shapiro-Wilk $p = 0.59$) but not of individuals with HD (Shapiro-Wilk $p = 0.007$) was log-normally distributed in our sample. Four potential outliers in the HD group did not differ in symptom severity from other HD participants (Fig. 6, 1-way ANOVA,

Table 2
Value-based model of choice using logistic panel data with random effects on initial 14 trials.

Predictor	β	Standard Error	Z-value	p-value
A. Choice model with all participants				
Constant	0.06	0.14	0.46	0.65
Expected value	0.03	0.04	0.80	0.43
Expected value × Diagnosis	0.11	0.07	1.69	0.09
Risk	− 0.17	0.05	− 3.46	0.00
Risk × Diagnosis	0.17	0.07	2.46	0.01
Loss	0.07	0.02	3.18	0.00
Loss × Diagnosis	− 0.05	0.03	− 1.95	0.05
Participants	38			
Periods	14			
Observations	532			
Log-likelihood	− 347.5			
Hosmer-Lemeshow χ2	26.21	*p-value*	< 0.001	
B. Choice model with Control participant only				
Constant	0.03	0.20	0.17	0.87
Expected value	0.03	0.04	0.72	0.47
Risk	−0.17	0.05	−3.28	0.00
Loss	0.07	0.02	3.12	0.00
Participants	19			
Periods	14			
Observations	266			
Log-likelihood	− 174.0			
Hosmer-Lemeshow χ2	15.55	*p-value*	0.05	
C. Choice model with HD participants only				
Constant	0.10	0.20	0.47	0.64
Expected value	0.15	0.05	2.92	0.00
Risk	− 0.01	0.05	− 0.20	0.84
Loss	0.02	0.02	1.14	0.26
Participants	19			
Periods	14			
Observations	266			
Log-likelihood	− 173.5			
Hosmer-Lemeshow χ2	12.89	*p-value*	0.12	

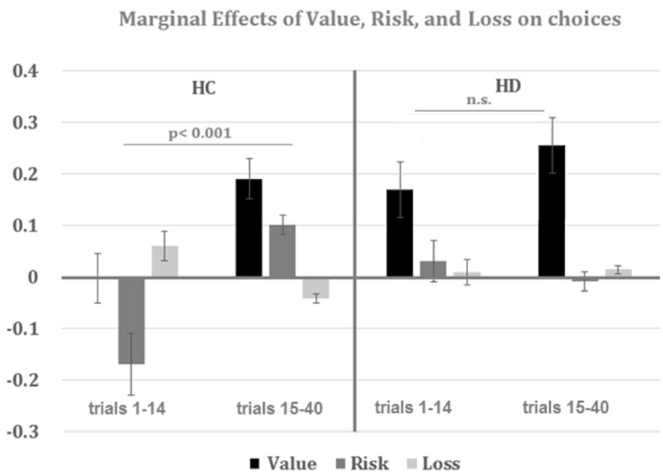

Fig. 5. Marginal Effects of Expected Value, Risk, and Anticipated Losses on choices.

Table 3
Value-based model of choice using logistic panel data with random effects on trials 15 through 40 (*steady state*).

Predictor	β	Standard Error	Z-value	p-value
A. Choice model with all participants				
Constant	0.08	0.13	0.65	0.51
Expected value	0.19	0.05	4.08	0.00
Expected value × Diagnosis	0.06	0.06	1.06	0.29
Risk	0.10	0.02	4.81	0.00
Risk × Diagnosis	− 0.07	0.02	− 2.80	0.01
Loss	− 0.05	0.01	− 5.03	0.00
Loss × Diagnosis	0.06	0.01	4.74	0.00
Participants	38			
Periods	26			
Observations	988			
Log-likelihood	− 620.9			
Hosmer-Lemeshow χ2	10.34	*p-value*	0.24	
B. Choice model with Control participant only				
Constant	0.07	0.18	0.39	0.70
Expected value	0.19	0.05	4.01	0.00
Risk	0.10	0.02	4.52	0.00
Loss	− 0.05	0.01	− 4.82	0.00
Participants	19			
Periods	26			
Observations	494			
Log-likelihood	− 358.2			
Hosmer-Lemeshow χ2	8.32	*p-value*	0.4	
C. Choice model with HD participants only				
Constant	0.10	0.19	0.53	0.60
Expected value	0.25	0.03	8.45	0.00
Risk	0.03	0.02	1.57	0.12
Loss	0.01	0.01	1.21	0.23
Participants	19			
Periods	26			
Observations	494			
Log-likelihood	− 362.8			
Hosmer-Lemeshow χ2	15.46	*p-value*	0.57	

$F(1, 15) = 0.4$, $p = 0.53$). Consistent with our predictions, individuals with HD took significantly longer to make choices than did HCs (Mann-Whitney U, $p = 0.006$,effect size $= 0.44$). At the same time, the two groups did not differ significantly in how many points they had earned during the experiment (mean for HD $= 91 \pm 15$and mean for HC $= 71 \pm 16$, $F(1,37) = 0.80$, $p = 0.38$). Note that nominally individuals with HD do appear to make on average more money (overall: mean_{HD} - $\text{mean}_{HC} = 20$, Cohen's $d = 0.30$). However, this difference was not significant in our sample, and the overall effect size was small. Thus, following a clear normative value-based rule throughout the experiment, as HD appeared to do, is not necessarily *ecologically rational*. That is, HD and HC earn about the same amount of money, but it takes HD much longer to do so; additional cognitive costs do not lead to additional benefits in this case.

3.3.2. Correlation between costs and benefits across participants

In exploratory analyses, we looked at the correlations between response time and payoffs across all participants throughout the experiments, and separately during initial trials and steady state trials. Overall, we found that response time (log-transformed) positively correlated with total payoffs (Spearman's $\rho = 0.396$, $p = 0.014$, Fig. 6). This appears to be driven by performance during the initial trials, during which correlation between response time (log-transformed) and payoffs was significant (Spearman's $\rho = 0.43$, $p = 0.006$, Fig. 6). Response time and payoffs did not correlate during the steady-state trials (Spearman's $\rho < 0.32$, $p > 0.18$, Fig. 6). Further exploration revealed that during the initial trials response time (log transformation) and payoffs correlated significantly only in HD (Spearman's $\rho = 0.58$, $p = 0.01$ for HD, and Spearman's $\rho = 0.34$, $p = 0.15$for HC). This may suggest that at least in some decision contexts (e.g. in the beginning of a new decision task) deliberating longer may have some short-term benefits for HD.

4. Discussion

This is the first study to propose and test the novel hypothesis that individuals with HD may be biased toward deliberative decision style in an ecologically inefficient manner. We contrasted decision making in individuals with HD and in HC during a gambling task that provides feedback, under risk. In this task, feedback can be used to evaluate and update the decision strategy. Consistent with prior studies (Brand, 2008; Brand et al., 2009; Schiebener and Brand, 2015; Shanks et al., 2002), we found that healthy individuals tend to explore in the beginning of the experiment, but later in the experiment, through trial-and-error, they shift towards more "rational" value-based strategies. In contrast, individuals with HD did not explore in the beginning of the task; instead, from the beginning to the end, they appeared to follow clear rules of value-based decision making irrespective of the feedback. This seemingly rational approach of individuals with HD did not appear to be *ecologically rational*. HD and HC earned about the same amount of money, but it took HD much longer to do it: additional cognitive costs did not lead to additional benefits.

Even during steady state, healthy individuals and individuals with hoarding perform differently. After initial exploration, healthy individuals tend to converge to a compound strategy: they balance their choices between maximizing expected value and minimizing risk. In contrast, individuals with HD appear to make their choices exclusively to maximize expected value, and appear to be unaffected by risk. This is in contrast to our recent findings that, when no feedback is provided, choices under risk of individuals with HD are not different from choices of HC (Pushkarskaya et al., 2017). It is consistent with previously reported difficulties with feedback processing in HD during WCST (McMillan et al., 2013; Pedron et al., 2015).

Our study does not provide insight into *why* individuals with hoarding rely on an ecologically irrational deliberative strategy when receive feedback on their choices. However, our novel *test of information processing style* in HD may provide new insights into complexity of hoarding symptomology. For instance, preference for a deliberative decision style has been associated with increased information seeking (Soane et al., 2015). We speculate that excessive acquisition in individuals with HD may not be limited to physical possessions but may extend to hoarding of information.

Costs imposed by a bias toward deliberative decision style may explain attentional deficits in individuals with HD (Hacker et al., 2016; Tolin and Villavicencio, 2011). Using ecologically rational strategies, especially during routine tasks, greatly reduces ongoing cognitive costs. In contrast, slow step-by-step deliberation during daily tasks may create a state of continuous cognitive overload. Cognitive load is associated with poor performance on tests of selective attention (Lavie et al., 2004) – exactly what is observed in individuals with HD.

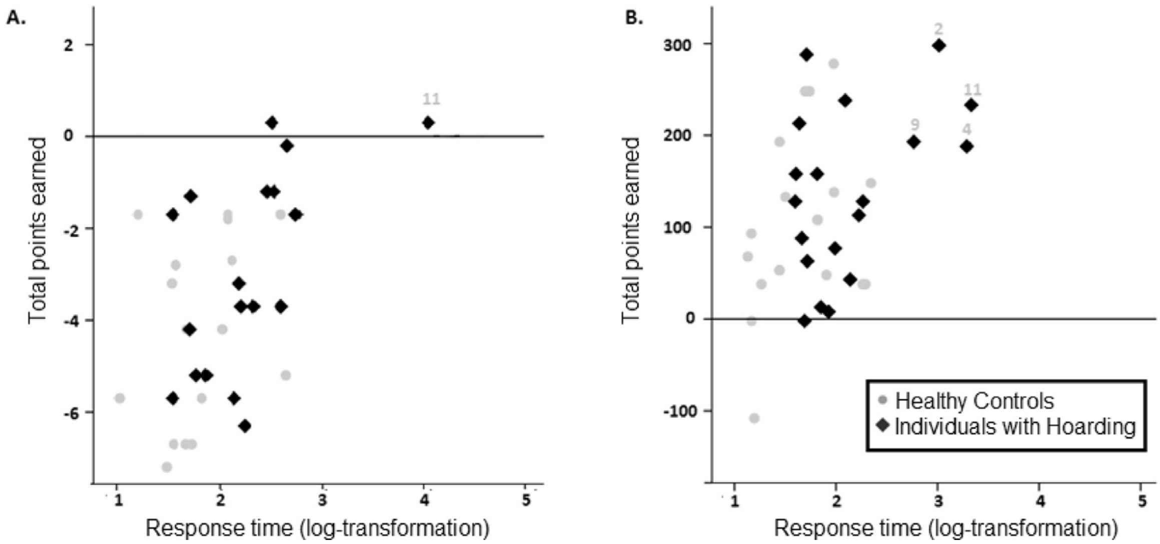

Fig. 6. Overall performance on the behavioral task during the initial trials (**A**) and the steady state (**B**) intervals: Response time and payoffs. Potential outliers (subjects 2, 4, 9, and 11) do not differ in clinical characteristics from the rest of HD participants.

Of note, exploratory analyses do suggest that deliberating longer may be beneficial for individuals with HD in some decision contexts (e.g. short term benefits during initial stages of novel tasks). In the very beginning of our experiment, individuals with HD who took longer to deliberate before making choices did earn more points than individuals with HD who made choices faster. This observation requires replication and further exploration. Such short-term benefits may be used by individuals with HD to rationalize the use of an ecologically irrational bias toward a deliberative strategy.

A rigid commitment to normative, deliberative decision making, at the expense of ecological rationality, may explain one of the most visible symptoms of compulsive hoarding: severe and persistent difficulty discarding or parting with possessions. The question a hoarder has to answer in order to decide whether to keep the item or not is often "What is the net expected value, in the future, of keeping this item?" A deliberative approach to this question requires consideration of all possible ways that the item can be used, and careful evaluation of the potential benefits of keeping the item under each circumstance. In real life, people never have enough information to answer such complicated questions in an exhaustive, deliberative way; life quickly provides them with feedback that such an approach is not optimal. Healthy people adapt; they switch to less normative but more ecologically rational strategies. We suggest that individuals with HD continue to rigidly follow a normative, ecologically irrational strategy, regardless of feedback. Given that complete information is not generally available in the real world, this may result in inability to make a decision – and thus the inability to discard. This may explain HD-related decision-making difficulties and slowness in real-world situations, despite normal behavior in many laboratory cognitive tasks.

One limitation of our study is that we make inferences about decision processes based on observed choices. This is a generally accepted approach in behavioral economics. However, further testing of our novel hypothesis of choice behavior in hoarding disorder using other approaches is warranted. For instance, we suggest that follow up studies test individuals with HD in tasks designed specifically to test the ability of individuals to employ ecologically rational strategies in response to contextual demands (Goldstein and Gigerenzer, 2002). These tasks, among other traits, examine individual ability to shift from suboptimal deliberative strategies to more effective heuristics-based strategies in response to received feedback.

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Author contributions

Helen Pushkarskaya – design, data collection and analysis, interpretation of the results, article preparation.

David Tolin - data collection, interpretation of the results, article preparation.

Daniel Henick - data collection, interpretation of the results, article preparation.

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Appendix A. Supplementary material

Supplementary data associated with this article can be found in the online version at http://dx.doi.org/10.1016/j.psychres.2017.11.001.

References

American Psychiatric Association, 2013. Diagnostic and Statistical Manual of Mental Disorders (DSM-5®). American Psychiatric Pub., Arlington, VA.

Brand, M., 2008. Does the feedback from previous trials influence current decisions? A study on the role of feedback processing in making decisions under explicit risk conditions. J. Neuropsychol. 2, 431–443. http://dx.doi.org/10.1348/174866407X220607.

Brand, M., Laier, C., Pawlikowski, M., Markowitsch, H.J., 2009. Decision making with and without feedback: the role of intelligence, strategies, executive functions, and cognitive styles. J. Clin. Exp. Neuropsychol. 31, 984–998. http://dx.doi.org/10.1080/13803390902776860.

Camille, N., Coricelli, G., Sallet, J., Pradat-Diehl, P., Duhamel, J.-R., Sirigu, A., 2004. The involvement of the orbitofrontal cortex in the experience of regret. Science 304, 1167–1170. http://dx.doi.org/10.1126/science.1094550.

Chu, C.-S.J., 1995. Time series segmentation: a sliding window approach. Inf. Sci. 85, 147–173. http://dx.doi.org/10.1016/0020-0255(95)00021-G.

Cohen, J., 1988. Statistical Power Analysis for the Behavioral Sciences. Lawrence Erlbaum Associates, Hillsdale, NJ.

Coricelli, G., Critchley, H.D., Joffily, M., O'Doherty, J.P., Sirigu, A., Dolan, R.J., 2005. Regret and its avoidance: a neuroimaging study of choice behavior. Nat. Neurosci. 8,

1255–1262. http://dx.doi.org/10.1038/nn1514.
Czerlinski, J., Gigerenzer, G., Goldstein, D.G., 1999. How Good are Simple Heuristics?
Dozier, M.E., Porter, B., Ayers, C.R., 2016. Age of onset and progression of hoarding symptoms in older adults with hoarding disorder. Aging Ment. Health 20, 736–742.
Freeston, M.H., Rhéaume, J., Letarte, H., Dugas, M.J., Ladouceur, R., 1994. Why do people worry? Personal. Individ. Differ. 17, 791–802. http://dx.doi.org/10.1016/0191-8869(94)90048-5.
Frost, R.O., Gross, R.C., 1993. The hoarding of possessions. Behav. Res. Ther. 31, 367–381. http://dx.doi.org/10.1016/0005-7967(93)90094-B.
Frost, R.O., Hartl, T.L., 1996. A cognitive-behavioral model of compulsive hoarding. Behav. Res. Ther. 34, 341–350. http://dx.doi.org/10.1016/0005-7967(95)00071-2.
Frost, R.O., Shows, D.L., 1993. The nature and measurement of compulsive indecisiveness. Behav. Res. Ther. 31http://dx.doi.org/10.1016/0005-7967(93)90121-A. (683-IN682).
Frost, R.O., Steketee, G., Grisham, J., 2004. Measurement of compulsive hoarding: saving inventory-revised. Behav. Res. Ther. 42, 1163–1182. http://dx.doi.org/10.1016/j.brat.2003.07.006.
Gigerenzer, G., Goldstein, D.G., 1996. Reasoning the fast and frugal way: models of bounded rationality. Psychol. Rev. 103, 650. http://dx.doi.org/10.1037/0033-295X.103.4.650.
Gillan, C.M., Morein-Zamir, S., Kaser, M., Fineberg, N.A., Sule, A., Sahakian, B.J., Cardinal, R.N., Robbins, T.W., 2014. Counterfactual processing of economic action-outcome alternatives in obsessive-compulsive disorder: further evidence of impaired goal-directed behavior. Biol. Psychiatry 75, 639–646. http://dx.doi.org/10.1016/j.biopsych.2013.01.018.
Goldstein, D.G., Gigerenzer, G., 2002. Models of ecological rationality: the recognition heuristic. Psychol. Rev. 109, 75. http://dx.doi.org/10.1037/0033-295X.109.1.75.
Grant, D.A., Berg, E., 1948. A behavioral analysis of degree of reinforcement and ease of shifting to new responses in a Weigl-type card-sorting problem. J. Exp. Psychol. 38, 404. http://dx.doi.org/10.1037/h0059831.
Grisham, J.R., Norberg, M.M., Williams, A.D., Certoma, S.P., Kadib, R., 2010. Categorization and cognitive deficits in compulsive hoarding. Behav. Res. Ther. 48, 866–872. http://dx.doi.org/10.1016/j.brat.2010.05.011.
Hacker, L.E., Park, J.M., Timpano, K.R., Cavitt, M.A., Alvaro, J.L., Lewin, A.B., Murphy, T.K., Storch, E.A., 2016. Hoarding in children with ADHD. J. Atten. Disord. 20, 617–626. http://dx.doi.org/10.1177/1087054712455845.
Kahneman, D., 2011. Thinking, Fast and Slow. Macmillan, New York, NY.
Kahneman, D., Slovic, P., Tversky, A., 1982. Judgment Under Uncertainty: Heuristics and Biases. Cambridge Univ. Press, Cambridge UK. http://dx.doi.org/10.1017/CBO9780511809477.
Kahneman, D., Tversky, A., 1979. Prospect theory: an analysis of decision under risk. Économ.: J. Econom. Soc. 263–291. http://dx.doi.org/10.2307/1914185.
Kaufman, A., 1979. Intelligent Testing. W/SC-R. Wiley-Interscience, New York.
Keogh, E., Chu, S., Hart, D., Pazzani, M., 2004. Segmenting time series: a survey and novel approach. Data Min. Time Ser. Databases 57, 1–22.
Kuo, W.-J., Sjöström, T., Chen, Y.-P., Wang, Y.-H., Huang, C.-Y., 2009. Intuition and deliberation: two systems for strategizing in the brain. Science 324, 519–522. http://dx.doi.org/10.1126/science.1165598.
Lavie, N., Hirst, A., De Fockert, J.W., Viding, E., 2004. Load theory of selective attention and cognitive control. J. Exp. Psychol.: Gen. 133, 339. http://dx.doi.org/10.1037/0096-3445.133.3.339. (PMid:15355143).
Mackin, R.S., Areán, P.A., Delucchi, K.L., Mathews, C.A., 2011. Cognitive functioning in individuals with severe compulsive hoarding behaviors and late life depression. Int. J. Geriatr. Psychiatry 26, 314–321. http://dx.doi.org/10.1002/gps.2531.
Mackin, R.S., Vigil, O., Insel, P., Kivowitz, A., Kupferman, E., Hough, C.M., Fekri, S., Crothers, R., Bickford, D., Delucchi, K.L., 2015. Patterns of clinically significant cognitive impairment in hoarding disorder. Depress. Anxiety 33 (3), 211–218. http://dx.doi.org/10.1002/da.22439.
McMillan, S.G., Rees, C.S., Pestell, C., 2013. An investigation of executive functioning, attention and working memory in compulsive hoarding. Behav. Cogn. Psychother. 41, 610–625. http://dx.doi.org/10.1017/S1352465812000835.
Morein-Zamir, S., Papmeyer, M., Pertusa, A., Chamberlain, S.R., Fineberg, N.A., Sahakian, B.J., Mataix-Cols, D., Robbins, T.W., 2014. The profile of executive function in OCD hoarders and hoarding disorder. Psychiatry Res. 215, 659–667. http://dx.doi.org/10.1016/j.psychres.2013.12.026.
Oglesby, M.E., Medley, A.N., Norr, A.M., Capron, D.W., Korte, K.J., Schmidt, N.B., 2013. Intolerance of uncertainty as a vulnerability factor for hoarding behaviors. J. Affect. Disord. 145, 227–231. http://dx.doi.org/10.1016/j.jad.2012.08.003.
Pedron, A.C., Ferrão, Y.A., Gurgel, L.G., Reppold, C.T., 2015. Relations between executive functions and different symptomatic dimensions in obsessive compulsive disorder. Paidéia 25, 229–239. http://dx.doi.org/10.1590/1982-43272561201511.
Petty, R.E., Cacioppo, J.T., Strathman, A.J., Priester, J.R., 2005. To think or not to think. Persuas.: Psychol. Insights Perspect. 81–116.
Pushkarskaya, H., Tolin, D., Ruderman, L., Henick, D., Kelly, J.M., Pittenger, C., Levy, I., 2017. Value-based decision making under uncertainty in hoarding and obsessive-compulsive disorders. Psychiatry Res. http://dx.doi.org/10.1016/j.psychres.2017.08.058.
Rangel, A., Camerer, C., Montague, P.R., 2008. A framework for studying the neurobiology of value-based decision making. Nat. Rev. Neurosci. 9 (7), 545–556.
Samuels, J., Bienvenu III, O.J., Riddle, M., Cullen, B., Grados, M., Liang, K.-Y., Hoehn-Saric, R., Nestadt, G., 2002. Hoarding in obsessive compulsive disorder: results from a case-control study. Behav. Res. Ther. 40, 517–528. http://dx.doi.org/10.1016/S0005-7967(01)00026-2.
Schiebener, J., Brand, M., 2015. Decision making under objective risk conditions–a review of cognitive and emotional correlates, strategies, feedback processing, and external influences. Neuropsychol. Rev. 25, 171–198. http://dx.doi.org/10.1007/s11065-015-9285-x.
Shanks, D.R., Tunney, R.J., McCarthy, J.D., 2002. A re-examination of probability matching and rational choice. J. Behav. Decis. Mak. 15, 233–250. http://dx.doi.org/10.1002/bdm.413.
Soane, E., Schubert, I., Lunn, R., Pollard, S., 2015. The relationship between information processing style and information seeking, and its moderation by affect and perceived usefulness: analysis vs. procrastination. Personal. Individ. Differ. 72, 72–78. http://dx.doi.org/10.1016/j.paid.2014.08.029.
Steketee, G., Frost, R., 2003. Compulsive hoarding: current status of the research. Clin. Psychol. Rev. 23, 905–927. http://dx.doi.org/10.1016/j.cpr.2003.08.002.
Sumner, J.M., Noack, C.G., Filoteo, J.V., Maddox, W.T., Saxena, S., 2015. Neurocognitive performance in unmedicated patients with hoarding disorder. Neuropsychology 30 (2), 157.
Tolin, D.F., 2011. Understanding and treating hoarding: a biopsychosocial perspective. J. Clin. Psychol. 67, 517–526. http://dx.doi.org/10.1002/jclp.20795.
Tolin, D.F., Gilliam, C., Wootton, B.M., Bowe, W., Bragdon, L.B., Davis, E., Hannan, S.E., Steinman, S.A., Worden, B., Hallion, L.S., 2016. Psychometric properties of a structured diagnostic interview for DSM-5 anxiety, mood, and obsessive-compulsive and related disorders. Assessment. http://dx.doi.org/10.1177/1073191116638410. (1073191116638410).
Tolin, D.F., Villavicencio, A., 2011. Inattention, but not OCD, predicts the core features of hoarding disorder. Behav. Res. Ther. 49, 120–125. http://dx.doi.org/10.1016/j.brat.2010.12.002.
Tolin, D.F., Villavicencio, A., Umbach, A., Kurtz, M.M., 2011. Neuropsychological functioning in hoarding disorder. Psychiatry Res. 189, 413–418. http://dx.doi.org/10.1016/j.psychres.2011.06.022.
Tversky, A., Kahneman, D., 1973. Availability: a heuristic for judging frequency and probability. Cogn. Psychol. 5, 207–232. http://dx.doi.org/10.1016/0010-0285(73)90033-9.
van der Linden, W.J., 2006. A lognormal model for response times on test items. J. Educ. Behav. Stat. 31, 181–204. http://dx.doi.org/10.3102/10769986031002181.
von Neumann, J., Morgenstern, O., 1944. Theory of Games and Economic Behavior. Princeton University Press, Princeton, NJ.
Wheaton, M.G., Abramowitz, J.S., Jacoby, R.J., Zwerling, J., Rodriguez, C.I., 2016. An investigation of the role of intolerance of uncertainty in hoarding symptoms. J. Affect. Disord. 193, 208–214. http://dx.doi.org/10.1016/j.jad.2015.12.047.