Shock to Thrill: Linking Sensation and Information Seeking

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Abstract

Sensation-seeking (SS) is characterised by a proclivity for intense experiences and disregard for potential aversive consequences. While SS is implicated as a vulnerability factor in various mental disorders, the underlying mechanisms remain elusive. Recent approaches propose an alternative perspective, suggesting that SS may be linked to highly explorative, and therefore risky, behaviours driven by a preference for informative environments. To probe this hypothesis, we reanalysed a dataset where participants chose to self-administer or avoid mild electric stimulation (MES) in an economic decision-making task. Contrary to previous interpretations associating higher sensation-seeking with the positive economic value of experiencing MES, Bayesian models of learning reveal an alternative account: sensation-seekers are more attuned to information about stimuli-shock contingencies. Specifically, high sensation-seeking individuals are less avoidant of information about the possibility of a shock, supporting the idea that sensation-seeking is linked to a preference for informative environments.

Keywords: Sensation-seeking; Reinforcement Learning; Information-seeking; Exploration/Exploitation; Computational Psychiatry

Introduction

Sensation-seeking (SS) is characterised by a preference for "varied, novel, complex, and intense sensations and experiences" often with a disregard for potential aversive consequences across physical, social, legal, and financial domains (Zuckerman, 1974). Notably, SS stands as a distinctive trait marked by highly explorative and risky behaviours during adolescence (Shulman, Harden, Chein, & Steinberg, 2015; Steinberg et al., 2008; Whiteside, Lynam, Miller, & Reynolds, 2005), and is a significant risk factor for engaging in a spectrum of activities associated with high societal costs and maladaptive outcomes (Chase & Ghane, 2023; Peritogiannis, 2015) such as alcohol/substance abuse (Evans-Polce, Schuler, Schulenberg, & Patrick, 2018; Hittner & Swickert, 2006), and antisocial behaviours (Hammerton et al., 2018; Mann et al., 2017). Intriguingly, recent evidence also suggests a link between SS and better psychological well-being (Ravert & Donnellan, 2021; Yoneda, Ames, & Leadbeater, 2019), with some studies linking SS to "positive risk-taking", indicating a developmentally normative and adaptive function (Duell & Steinberg, 2020, 2021; Hansen & Breivik, 2001; Fischer & Smith, 2004). SS has also been shown to have neurobiological correlates, with dopamine (DA) associated with individual differences in SS levels (Norbury, Kurth-Nelson, Winston, Roiser, & Husain, 2015), with high sensation seekers exhibiting elevated extracellular DA and receptors in the caudate nucleus, accompanied by attenuated DA turnover rates (Chang et al., 2022). Still, the precise conditions for dysfunction remain unclear.

Despite predicting a wide range of risky behaviours, the precise mechanisms that set SS apart as a distinctive trait remain enigmatic. Bridging this gap is a central goal in computational psychiatry, where a comprehensive computational explanation of SS holds the potential to unravel the mechanisms involved. An explicit computational account can provide insights into how these mechanisms deviate from optimality, offering better objective markers for diagnosis, prevention, and future treatment (Huys, Maia, & Frank, 2016; Hauser, Skvortsova, De Choudhury, & Koutsouleris, 2022; Stephan & Mathys, 2014).

Recent Perspectives. The association between risky behaviours and high exploration suggests that the exploration-exploitation trade-off (Addicott, Pearson, Sweitzer, Barack, & Platt, 2017) may be vital to understanding the underlying mechanisms of SS. Exploitation maximises short-term rewards by choosing familiar options, while exploration involves trying uncertain but potentially higher-payoff alternatives. Excessive exploitation limits information gathering, fostering inflexibility, while too much exploration leads to risky decision-making and reduced long-term payoffs. Striking a balance between these strategies is vital for long-term reward optimisation (Mehlhorn et al., 2015).

Research in this domain has found evidence for two distinct and dissociable forms of exploration: random and directed exploration (Gershman, 2018; Wu, Schulz, Pleskac, & Speekenbrink, 2022; Zajkowski, Kossut, & Wilson, 2017; Wilson, Geana, White, Ludvig, & Cohen, 2014). Random exploration involves a stochastic selection of sub-optimal options, often modelled with softmax functions and temperature parameters (Daw, O'Doherty, Dayan, Seymour, & Dolan, 2006). In contrast, directed exploration is strategic, informed by the subjective uncertainty of an option, often using Bayesian learning models (Speekenbrink & Konstantinidis, 2015; Wu, Schulz, Speekenbrink, Nelson, & Meder, 2018). Thus, while risky, uncertainty-guided exploration serves an information-seeking goal, with highly uncertain options likely to result in valuable information transfer from the

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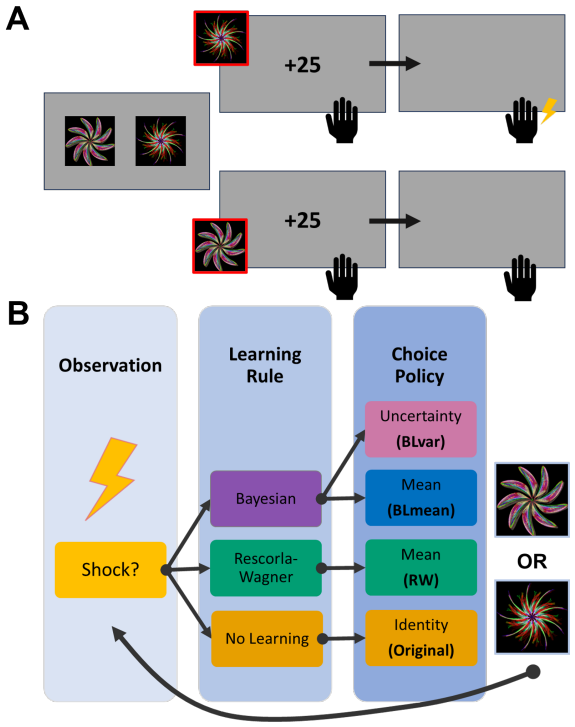

Figure 1: (**A**) Overview of task. Participants were presented with a series of two alternative forced-choice decisions. There were a total of 8 different bandits, each assigned points 25, 50, 75, or 100. These point-stimuli associations were learnt during a prior acquisition phase. For the test phase, half of the bandits were then associated with a mild probabilistic electric shock (CS+) and were always paired in each trial with a bandit with no shock (CS-). (**B**) Overview of computational models. Each model consisted of a learning rule (Bayesian vs Rescorla-Wagner vs No-Learning) and a choice policy (based on mean or uncertainty).

environment to the individual (Cogliati Dezza, Schulz, & Wu, 2022; Giron et al., 2023).

The explore-exploit dilemma has been a helpful framework in demonstrating that risk-seeking traits such as impulsivity are linked to heightened "value-free" random exploration (Dubois & Hauser, 2022). However, which form of exploration sensation-seekers engage in remains an open question. A recent review by Chase and Ghane (2023) suggests that SS may be associated with a preference for highly informative environments, suggesting uncertainty-directed exploration towards learning environments. Although sensation-seekers have been shown to seek more information in experimental tasks (Henderson, Hennessy, Barrett, Martin, & Fishbein, 2006), rigorous and mechanical testing of this hypothesis using computational modelling is currently lacking.

Goals and Scope. Here, we reanalyse data from Norbury et al. (2015) to demonstrate an alternative account of their results. In their investigation, participants engaged in a simple economic decision-making task with probabilistic self-administered electric shocks. Both economic value and shock contingencies were learned through trial and error. Utilising computational modelling, the researchers observed that individuals with high SS scores were more likely to assign a positive value to Mild Electric Stimulation (MES).

However, their approach has certain limitations that warrant further investigation. Firstly, their computational model overlooked the learning dynamics related to MES contingencies, deviating from the task design where participants needed to learn shock associations through trial and error. Secondly, a plausible alternative explanation exists: the choice to administer MES might be due to uncertainty exploration for learning shock contingencies. Therefore, we aim to extend these previous findings by exploring the role of information-seeking. We ask whether the decision to self-administer MES is rooted in an economic valuation or due to an uncertainty-driven learning motive. Moreover, if the latter holds, does uncertainty-driven exploration also emerge as a more robust predictor of sensation seeking, and how is this influenced under a dopamine antagonist?

Methods

We reanalyse a dataset previously collected by Norbury et al. (2015) to test the hypothesis that sensation-seeking is related to information-seeking via uncertainty-guided exploration. Here, we briefly overview the task design and participant demographics.

In Study 1, 45 healthy subjects (28 females, mean age = 24.3 $\pm$ 3.55) were recruited to investigate CS+ choice bias and self-reported sensation-seeking. Participants completed a revised version of the Sensation-Seeking Scale (SSS-V) version V (Zuckerman, 1994; Gray & Wilson, 2007). The SSS-V consists of four subscales: thrill and adventure seeking, experience seeking, disinhibition, and border susceptibility, from which overall SS was calculated as a sum across all four measures. Behavioural data from three subjects were excluded, and sensation-seeking scores were not recorded for six participants, resulting in 39 subjects available for reanalysis.

In Study 2, 30 healthy male participants were recruited (mean age = 22.3 $\pm$ 2.74) to investigate the effects of a dopamine antagonist on CS+ choice. Behavioural data from 2 subjects were excluded in the original paper, leaving 28 subjects available. All subjects completed 3 sessions of the sensation-seeking task. The first was a baseline and subsequently counterbalanced between placebo and haloperidol (2.5mg). During the pre-screening procedure, participants filled out the SSS-V and additionally completed the UPPS impulsivity questionnaire (Whiteside & Lynam, 2001), featuring subscales for sensation-seeking and three other impulsivity facets.

Sensation-Seeking Task. The experiment employed a two-phase, two-armed bandit task to study the economic value individuals attribute to receiving an intense sensory stimulus—specifically, a mild, non-painful electric shock (MES; Fig. 1A). In the acquisition phase, participants underwent the process of learning the point values associated with eight bandits. This phase extended for a minimum of 80 trials until participants met a predefined criterion level of performance.

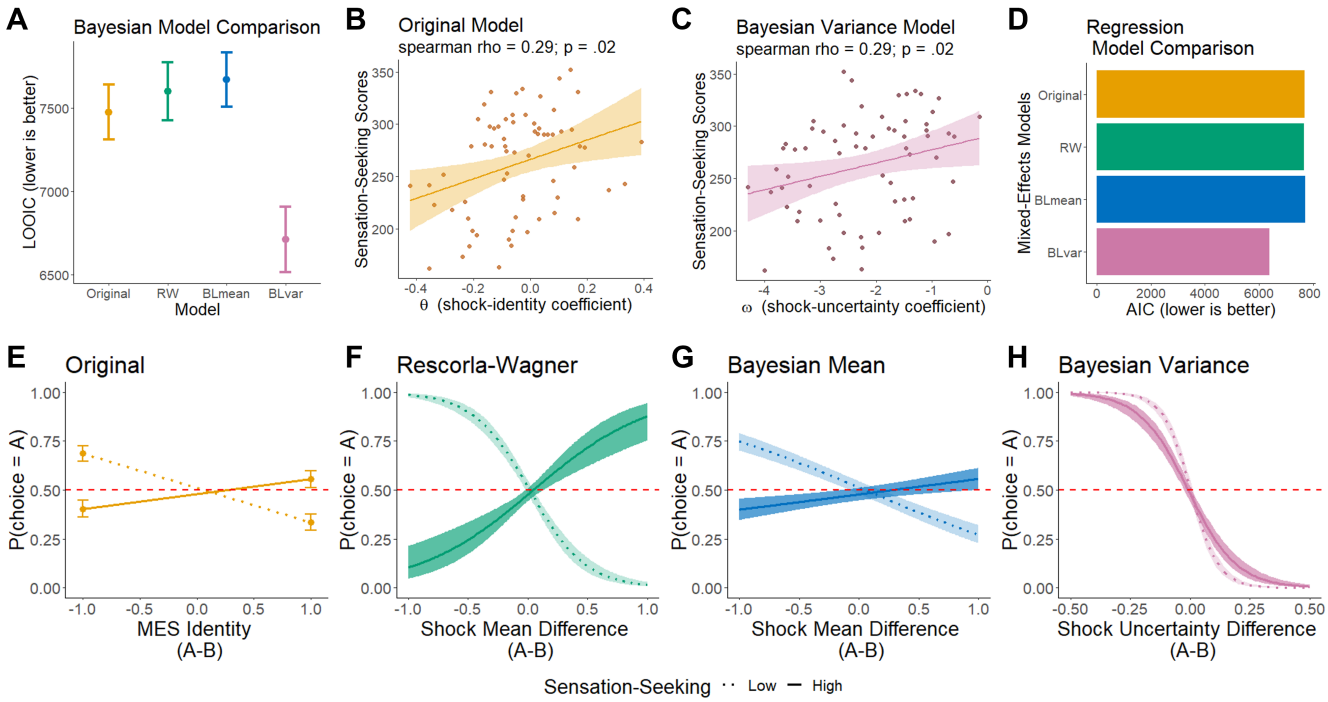

Figure 2: (**A**) Leave-one-out information criteria (LOO-IC) with lower values indicating better fits. The best-fitting model incorporated Bayesian learning with a variance choice rule (BLvar). (**B**) We replicated the main findings from Norbury et al. (2015) using pooled data and a Hierarchical Bayesian Modeling (HBM) procedure, although it was not the best model. (**C**) Significant associations were observed between ω parameters estimated from the BLvar model and self-reported sensation-seeking ($\rho = 0.29$, $p = .02$). (**D**) AIC of mixed-effects logistic regressions show that the model incorporating differences in uncertainty estimated from Bayesian Learning (BL) and its interactions with SS scores performed the best. The probability of choice A in a given test trial was examined as a function of differences in (**E**) MES identity, (**F**) estimated shock mean under Rescorla-Wagner learning, (**G**) estimated shock mean under BL, (**H**) estimated shock uncertainty under BL and their respective interactions with SS levels. Across **E** to **H**, each line represents the fixed effect of a mixed-effects regression grouped by high sensation seekers (bold line) and low sensation seekers (dotted line) based on a mean split, with ribbons indicating 95% confidence intervals (CI). The red dotted lines indicate the chance level.

Two of these bandits were assigned to each of four possible point values (25, 50, 75, or 100 points). Presented as pairs in every trial, the bandits yielded 10 trial types.

Crucially, the CS+ bandit was consistently paired with another CS- bandit, creating three distinct scenarios: when the CS+ bandit offered a greater monetary payoff than the CS- (3 trial types) when it provided a lower payoff (3 trial types), and when they were equal (4 trial types). Subsequently, in the test phase, half of the bandits became associated with a 0.75 chance of receiving MES to the hand (CS+), while the others did not (CS-). Participants completed 100 test phase trials, encompassing 10 trials of each trial type. This design facilitated the observation of participants' choice patterns to discern any bias toward the CS+ bandits.

Before commencing the task, participants provided ratings of their preference for each bandit intended for use in the paradigm on a computerised visual analogue scale (VAS) ranging from "like" to "dislike". This measure was repeated a second time after the acquisition phase (i.e., after learning the point values associated with each CS) and a third time at the end of the experiment (i.e., following the introduction of MES). The mean difference between the third and second ratings indicated overall MES-liking.

Computational Models

Computational modelling was used to understand the decision-making processes related to MES stimuli. These models encompass a *learning component*, utilising either Rescorla-Wagner or Bayesian methods, which define how the expected probability of shock is updated following observations and a *choice rule* formulated as a linear combination of model features (Fig. 1B). We also briefly describe the original model in Norbury et al. (2015) that modelled no learning. During an initial acquisition phase, subjects acquired knowledge of the point payoffs associated with each bandit, denoted as V_j. This phase consisted of a minimum of 80 trials, with a performance criterion requiring the selection of the bandit associated with the higher point value in 80% or more of the last ten trials. Thus, these payoffs are presumed to be fully known.

Original Economic Model. The modelling approach described by Norbury et al. (2015) involved the representation

of Q-values for each bandit as a combination of their monetary payoff and an additional value, θ if the bandit is associated with MES:

$$Q_j = V_j + \theta I_j, \tag{1}$$

where $I_j = 1$ if bandit j is associated with MES, and 0 otherwise. Note that this approach does not model the learning process, but instead assigns a fixed, binary value to each bandit based on the identity I_j.

Rescorla-Wagner Learning Model. We use a Rescorla-Wagner (RW) learning model (Rescorla, 1972) to model the trial-and-error learning process of shock contingencies. Specifically, the estimated probability of shock of the chosen bandit after each trial is updated according to a prediction error δ scaled by the learning rate λ. The prediction error δ reflects the discrepancy between the expected probability of shock at trial t and the outcome $S_{j,t}$.

$$\mu_{j,t+1} = \mu_{j,t} + \lambda\delta, \text{ where } \delta = S_{j,t} - \mu_{j,t} \tag{2}$$

Bayesian Learning Model. To quantify subjective uncertainty, we implemented a Bayesian model that assumes shock probabilities for each bandit j are represented as beta distributions. This approach is most appropriate for learning probabilities since the distribution is between 0 and 1, and the variance estimates uncertainty. Similar models have previously been used to model value-based learning (de Boer et al., 2017) and aversive learning tasks (Wise & Dolan, 2020; Wise, Michely, Dayan, & Dolan, 2019).

$$P_{j,t}(shock) \sim Beta(\alpha_{j,t}, \beta_{j,t}) \tag{3}$$

Intuitively, the model describes how the evidence for MES depends on the number of shocks previously delivered. These counts can be represented for each bandit by the parameter α_j, which is incremented depending on whether a shock is delivered ($S_{j,t} = 1$). Similarly, the counts of no shocks ($S_{j,t} = 0$) are tracked by a complementary parameter β_j. For simplicity, we assume optimal updating, where α and β are updated by a value of 1 after observing the respective outcome:

$$\alpha_{j,t+1} = \alpha_{j,t} + S_{j,t} \tag{4}$$

$$\beta_{j,t+1} = \beta_{j,t} + (1 - S_{j,t}) \tag{5}$$

The expected probability of shock μ for bandit j at trial t is:

$$\mu_{j,t} = \frac{\alpha_{j,t}}{\alpha_{j,t} + \beta_{j,t}} \tag{6}$$

and the associated uncertainty σ is:

$$\sigma_{j,t} = \sqrt{\frac{\alpha_{j,t}\beta_{j,t}}{(\alpha_{j,t} + \beta_{j,t})^2(\alpha_{j,t} + \beta_{j,t} + 1)}} \tag{7}$$

Choice Rules. Q-values for each bandit j were calculated as a linear sum of their underlying monetary payoff V_j and either the estimated mean probability of shock, μ_j, scaled by free parameter θ, or the associated uncertainty σ_j, scaled by free parameter ω.

For mean shock probabilities, μ_j, derived from Rescorla-Wagner and Bayesian learning processes, the overall Q-values are calculated as follows:

$$Q_j = V_j + \theta\mu_j \tag{8}$$

For estimated uncertainty, σ_j, derived from the Bayesian learning processes, the overall Q-values are calculated as follows:

$$Q_j = V_j + \omega\sigma_j \tag{9}$$

Given bandits A and B, the probability of choosing bandit A at trial t is given by a softmax function controlled by the temperature parameter τ.

$$P(choice_t = A) = \frac{e^{Q_A/\tau}}{e^{Q_A/\tau} + e^{Q_B/\tau}} \tag{10}$$

Model Fitting and Comparison

We derived four models based on different combinations of learning rules and choice policies (Fig. 1B): the original Norbury model (Original), the Rescorla-Wagner with mean policy (RW), Bayesian with mean Policy (BLmean), and Bayesian with uncertainty policy (BLvar). All models were estimated hierarchically using custom-written STAN code. Specifically, we used Hamiltonian MCMC with a No-U-Turn sampler to estimate the group-level mean, μ_0, and variance σ_0^2 for all model parameters among participants. Weakly informative $N \sim (0,1)$ priors were assigned to group-level parameters. Chain convergence was assessed using the $\widehat{R}$ statistic, where $1 \leq \widehat{R} \leq 1.01$ were acceptable. The model was estimated over four chains of 4000 iterations, with a burn-in period of 1000 samples and a proposal acceptance probability set to 0.99. The point payoff for all bandits was scaled between $[0,1]$ before fitting.

Model comparison was conducted using the loo package in R, leveraging a version of the loo estimate optimised through Pareto smoothed importance sampling (PSIS) methodology (Vehtari, Gelman, & Gabry, 2017). The loo approach assesses the out-of-sample predictive accuracy of the model, essentially evaluating how well the entire dataset, excluding one data point, predicts the outcome for the excluded point.

Results

Experiment 1

To increase the sensitivity of our analysis, we pooled data from 45 subjects in Study 1 and 28 subjects from the baseline session of Study 2 to give 73 subjects overall.

Model-based analysis. We used computational models to assess if sensation-seekers were guided by the value assigned to the estimated mean probability of shock or the uncertainty of shock. To this end, we developed five models, each with a combination of learning mechanisms and choice policies (Fig. 1B). Using Bayesian model selection, we found that the Bayesian learning model with the uncertainty choice policy (BLvar; Fig. 2A) made the best overall predictions.

While we were able to reproduce the results of the Norbury et al. (2015) study showing SS scores were related to the expected probability of shock ($\rho = 0.29$, $p = .02$; Fig. 2B), we found equally strong correlations for the winning BLVar model, but for the ω coefficients defining the influence of shock uncertainty ($\rho = 0.29$, $p = .02$; Fig. 2C). To delve into SSS-V subscores, ω estimates were significantly correlated with experience-seeking ($\rho = 0.31$, $p = .01$) and disinhibition ($\rho = 0.25$, $p = .04$), but not with thrill-and-adventure seeking ($\rho = 0.22$, $p = .07$) and boredom susceptibility ($\rho = 0.15$, $p = .21$). Since estimated coefficients were negative (Fig. 2C), these results do not point towards a firm definition of information seeking but rather reduced information avoidance. Specifically, individuals with high self-report SS scores were less likely to avoid information about MES. Unlike the original paper, we could not find correlations between ω and MES-liking (spearman's $\rho = 0.06$, $p = .61$). This makes sense, as MES-liking did not correlate with SS scores in the first place (spearman's $\rho = -0.01$, $p = 0.91$). This suggests that other underlying mechanisms may be at play. Surprisingly, relative choice RT for MES-associated vs non–MES–associated stimuli also did not correlate with ω estimates (spearman's $\rho = 0.23$, $p = 0.05$), despite being correlated with SS scores (Pearson's $r = -0.30$, $p = .01$).

Response curve analysis. We constructed a series of mixed-effects logistic regression models to assess the impact of subjective mean shock probability and shock uncertainty on the probability of choosing an option in a given trial (Fig. 2D-H). We explored how the probability of choice A was influenced by point payoff, and either MES identity (Original; Fig. 2E), estimated shock probability (RW and BLmean; Fig. 2F-G) or shock uncertainty (BLvar; Fig. 2H), including interactions with SS scores. Accounting for individual variations, we incorporated a random effects structure, allowing us to specify the influence of either shock probability or uncertainty in estimated marginal means. Contrast analyses were employed to quantify differences in the dependent variable marginalised over variations in point payoff.

Ranking AIC scores, the best model was the BLvar model using shock uncertainty and interaction with SS scores (AIC: 6394.9; Fig. 2D). Overall, there was a negative relationship between the probability of selecting choice A and the difference in uncertainty ($EMM = -13.56 \pm 0.44$, $Z = -31.09$, $p < .001$), indicating that participants tended to avoid bandits with greater shock uncertainty. However, this trend was less pronounced among individuals with high sensation-seeking tendencies ($EMM = 1.84 \pm 0.43$, $Z = 4.26$, $p < .001$), who had flatter curves.

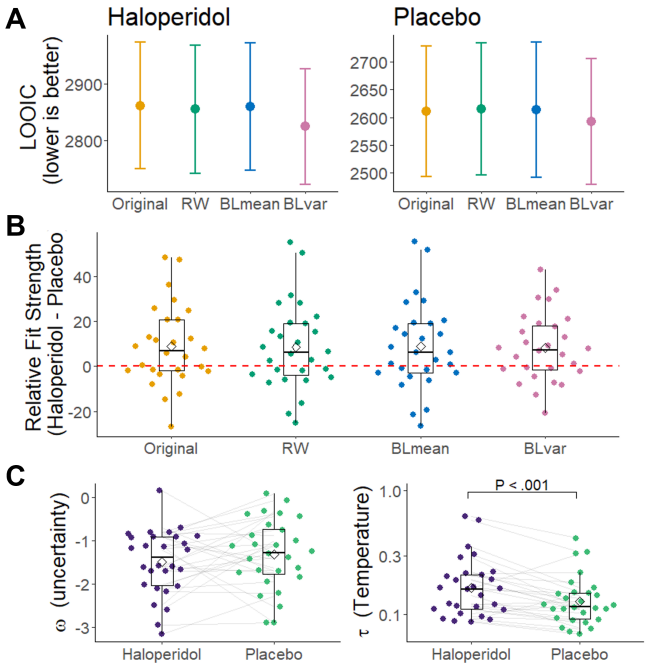

Figure 3: (**A**) Leave-one-out information criteria (LOO-IC) comparison. Lower values indicate better fits. The Bayesian learning rule with the variance choice policy (BLvar) was again found to be the best-fitting model across conditions. (**B**) Fit strength was lower in the haloperidol condition (all $p < .05$), but model ranking had no observable changes. (**C**) Group differences in model parameters were evaluated using paired-sample t-tests. Higher ω estimates indicate less uncertainty avoidance. Higher temperature τ estimates (log-scale) indicate greater choice stochasticity. Each connected dot represents a participant, and Tukey boxplots are overlaid with the diamond indicating the group mean.

Experiment 2

Drug effects on parameter estimates. Data from 28 subjects were analysed to investigate the effect of haloperidol on uncertainty-guided exploration. Across both drug conditions, the model comparison showed that the Bayesian learning model with variance choice policy was again the winning model, albeit marginally (BLvar; Fig. 3A). By comparing the relative fit strengths between haloperidol against placebo conditions, fits were worse under treatment (all $p < .05$; Fig .3B). We compared drug group differences using paired sample t-tests (Fig. 3B) but did not find differences in drug group differences in ω estimates ($M = 0.18 \pm 0.18$, $t(27) = -1.02$, $p = .32$), suggesting administration of a dopamine antagonist did not influence levels of information avoidance. However, we found a significant increase in τ estimates under haloperidol ($M = 0.05 \pm 0.02$, $t(27) = -3.94$, $p < .001$), suggesting that participants were more stochastic in their choices under a dopamine antagonist (Fig. 3C), which may have also driven the poorer model fits.

Discussion

We build upon previous findings by investigating whether the estimated mean shock probability or shock uncertainty could better explain the probability of choosing MES. Across both behavioural and model-based analyses, we consistently found that MES choice is more strongly influenced by uncertainty than by the mean. Our results revealed that participants assign a negative value to shock uncertainty. This suggests an overall tendency for subjects to avoid information related to shock probabilities for each bandit, with high sensation seekers being less avoidant than low sensation seekers.

A surprising observation in our study was that the learning models of shock probabilities, specifically the Rescorla-Wagner (RW) and Bayesian Learning with Mean policy (BLMean), did not yield a better fit compared to the original model (Original). This suggests that no substantial learning of shock contingencies occurred contrary to the trial-and-error learning expected of participants. One possible explanation for this discrepancy could be that the task design had an inherent structure (i.e. in every trial, MES and non-MES bandits were consistently paired). Participants might have developed an explicit representation of this task structure, facilitating model-based learning. This explicit representation could have allowed participants to make more statistically efficient use of information, contrary to the model-free learning assumed in our current models (Castro-Rodrigues et al., 2022).

Associations with Sensation-Seeking. By correlating SS scores with ω parameters, we demonstrated that high SS is associated with less information avoidance (Fig.2 B). While this does not indicate a firm definition of information-seeking, it still suggests that high sensation-seekers are more susceptible to making decisions where information is non-instrumental or potentially harmful. One reason for the absence of a clear information-seeking motive may be the sampling from an overall healthy population. Future studies could consider an extreme group strategy or sample from demographics that typically exhibit high levels of SS, such as extreme sports enthusiasts or clinical populations.

Furthermore, SS is a multidimensional construct, encompassing dimensions of thrill and adventure seeking (TAS), experience seeking (ES), disinhibition (DIS), and boredom susceptibility (BS). Therefore, it is improbable that trait SS solely aligns with uncertainty/information preference. This is evident as ω estimates loaded onto some SS subscales such as ES and DIS, but not TAS and BS. Additionally, we were unable to replicate associations between ω estimates and relative reaction times for MES vs non-MES-associated stimuli, thereby missing insight into approach-withdrawal mechanisms in response to novel and intense stimuli among sensation seekers (Zuckerman, 1990). As such, it is important to consider other SS mechanisms and their potential interactions. For instance, SS has been repeatedly shown to be associated with heightened reward sensitivity (Hawes et al., 2017; Tapia León, Kruse, Stark, & Klucken, 2019; Harden et al., 2018) and elevated tolerance to losses (Zheng, Tian, Li, & Liu, 2019) that cannot be solely accounted for by an information-seeking account. Considering all these components would be needed to model the full SS phenotype.

Haloperidol Effects. We failed to find significant changes in ω estimates under Haloperidol (i.e., consistent levels of uncertainty avoidance), but we found it increased temperature τ (i.e., more stochastic decisions). This may initially appear counterintuitive in light of the established role played by DA in the exploration/exploitation trade-off (Kayser, Mitchell, Weinstein, & Frank, 2015). However, studies have associated both directed and random exploration with genetic variations influencing prefrontal and striatal DA levels, with individuals presumed to have higher DA tone exhibiting heightened exploration (Gershman & Tzovaras, 2018). Consequently, one would expect a DA antagonist like haloperidol to lead to increased exploitative choices and reduced decision stochasticity. However, previous research utilising DA antagonists as a pharmacological intervention on exploratory behaviours has been mixed, with some reporting no effects on levels of exploration (Chakroun, Mathar, Wiehler, Ganzer, & Peters, 2020; Pine, Shiner, Seymour, & Dolan, 2010) or even reversed effects (Cinotti et al., 2019; Lee, Seo, Dal Monte, & Averbeck, 2015). The observed reversal of effects might be attributed to the potential of single, low doses of haloperidol (2.5mg) to increase DA release via action on presynaptic D2 autoreceptors (Eisenegger et al., 2014; Ford, 2014). This contrasts with the antidopaminergic effects observed under chronic and high-dose treatment (Frank & O'Reilly, 2006; Dubois et al., 2021), offering a plausible explanation for the observed increase in decision stochasticity.

Limitations and Future Directions. However, several limitations should be acknowledged. Specifically, investigating the joint effect of shock mean and uncertainty on choice patterns was challenging due to collinearity in the experimental design: CS- had no MES possibility, leading to no variability in MES delivery, while CS+ had probabilistic shocks and higher variability. Consequently, a full model incorporating both mean and uncertainty in the choice policy was nonidentifiable. Although our reanalysis leans towards supporting the uncertainty account, future experiments should strive to orthogonalise the effects of uncertainty and rewards/punishments to elucidate their contributions to SS.

Conclusions. Overall, we find stronger evidence that MES choice is guided by shock uncertainty rather than shock value. Additionally, we present initial evidence suggesting that individuals with higher SS traits exhibit less uncertainty avoidance, emphasising a potential link between SS and information-seeking behaviour. However, our investigation revealed no discernible alteration in uncertainty avoidance under the dopamine antagonist haloperidol but rather an increase in choice stochasticity. Taken together, we establish a link between trait SS, uncertainty, and decision-making processes, shedding light on underlying mechanistic processes that may better inform psychiatric diagnoses and treatments.

Code and Data Availability

The data supporting the findings of this study can be requested from the authors of Norbury et al. (2015). The data are not publicly available due to ethical guidelines. All STAN models described in the paper are uploaded to https://github.com/ErnWg/cogsci_sensationseeking.

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