# Bayesian Decision-Making Under Uncertainty in Borderline Personality Disorder

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## ABSTRACT

Existing research presents a working understanding of Borderline Personality Disorder (BPD) patients' symptomatology, traits, and behavior in everyday life, but how they combine and utilize prior and likelihood (current sensory) information when making decisions remains unclear. Bayesian Decision Theory suggests that optimal decision-making behavior should combine and weigh both pieces of information according to their relative uncertainties, such that people rely more on the information with less uncertainty when making a decision. Though this optimal behavior has been observed in neuro-typical populations, prior literature suggests that certain neuro-atypical populations can deviate. Some characteristics of BPD patients, such as impulsive behavior and fast drastic changes in the overall perception of themselves and others, suggest that they may be over-relying on likelihood information and not sufficiently taking prior information into account. From a Bayesian perspective, this can be interpreted as having 'weak' priors which may lead to suboptimal decision-making. Here, we investigated this hypothesis by having BPD patients (n = 23) and healthy controls (n = 18) perform a coin-catching sensorimotor task with varying levels of prior and likelihood information uncertainty. Our results indicate that, contrary to our prediction, BPD patients were able to use prior information, and that their use of prior and likelihood information follows qualitatively Bayesian behavior. We found that BPD patients, at least in a lower-level and non-affective sensorimotor task, are still able to use both prior and likelihood information and react appropriately to the respective uncertainties. This suggests that any potential deficits in the use of prior information may not be widespread or only be apparent in affectively-charged interpersonal contexts.



**Keywords:** Bayes; uncertainty; prior; likelihood; Borderline Personality Disorder; Decision-making

## Introduction

Every day we are required to make decisions, ranging from trivial ones such as what to wear to work to more paramount ones such as which career path to take. A variety of information can be used to make such decisions - information on potential rewards and losses, time constraints, probabilities of different outcomes, etc. Bayesian Decision Theory offers a framework that focuses on the specific types of information people use: prior information and current sensory information. Prior information refers to the knowledge that we have gained from previous experiences in similar settings (1). Current sensory information, also known as likelihood information, refers to the current input that we are receiving at any given moment. The way we utilize prior and likelihood information depends on how reliable we think each type of information is (1). For example, suppose the outcomes of our previous decisions have not been consistent or have been difficult to predict. In this situation, since our prior information comes with more uncertainty, we may rely more on likelihood information to make our present decision. Likewise, if the likelihood information we are receiving seems to be more unreliable, we may tend to rely more on prior knowledge to guide our current decision-making behavior. Previous literature has generally found that those considered to be neuro-typical can make decisions in this Bayesian-optimal manner, by appropriately utilizing the information's relative levels of uncertainty, as predicted by Bayesian Decision Theory (1–10). In addition, there is evidence in support of the independent encoding and distinct representation of these two types of information in the brain (11–13). There is also evidence that suggests that prior information can be learned independently from likelihood information in a way that is similar to the optimal manner as predicted by Bayesian statistics (14). This provides a basis in support of Bayesian-like information usage in decision-making for neuro-typical adults. However, this may not be the case for non-neurotypical populations including Parkinson's Disease and Autism Spectrum Disorder patients (15–20). Similarly, little is known about how people with personality disorders, namely Borderline Personality Disorder (BPD), combine prior and likelihood information.

BPD, found in approximately 1.7% of the general population, is characterized by heightened sensitivity to perceived interpersonal slights, unstable perception of self and others, volatile moods, and impulsive behavior. These characteristics typically lend themselves to maladaptive outcomes (21,22). For example, a minor slight such as showing up late to a meeting once or making a one-off blunt remark may drastically change a BPD patient's opinion of a person they have known for years. From a Bayesian decision-making standpoint, this could be interpreted as relying more on likelihoods and less on priors, and/or an over-updating of priors. In general, the unstable perception about both self and others, one of the hallmarks of BPD, could be interpreted as an improper reliance on priors, or even an incapacity to build them in the first place. This may lead to a number of negative outcomes in everyday life for those with BPD, ranging from trivial ones such as losing a networking opportunity to more serious ones such as losing important relationships both at work and at home.

Existing research shows some evidence for improper prior formation or updating in social settings in BDP patients. For example, some studies suggest that participants with BPD display more malevolent representations of others' emotions, intentions, and behavior (23,24). BPD patients have also been found to trust less and have significantly lower expectations for the payoff in a two-person trust game (25). In addition, when asked to rate faces they rated them as less approachable and less trustworthy than how controls rated them (26). A recent study by Siegel and colleagues found that the belief (prior) updating may differ between BPD patients and controls, and that this difference may depend on the perceived character of the person/agent they are judging (27). In their study, participants saw the decisions of two agents (a "good" and a "bad" agent) that were willing (or not) to harm others for money and had to periodically rate their subjective impressions of both the morality of the observed agent as well as how certain they were about it. They found that, although there were no significant differences in overall judgments of character, untreated BPD patients were more certain about their negative beliefs of the "bad" agent and, furthermore, updated these beliefs less. The opposite happened with the "good" agent, which seemed to update their beliefs faster than controls, with no significant difference in the certainty of those beliefs. Altogether, these studies suggest that BPD patients have improper (e.g. more negative) priors of others, and that they may update them differently.

The significant role and impact of BPD characteristics can be seen clearly within social settings, but it is not as well understood within non-social settings. In a delay-discounting task, BPD patients were found to have a greater rate of discounting than control participants without BPD. This was associated with overall impulsiveness and non-planning impulsiveness. These results suggest that BPD may be characterized by a bias towards immediate rewards (28). Those with BPD have also been shown to have impaired decision-making abilities. Relative to those without BPD, patients with BPD were found to make less advantageous choices in the Iowa Gambling Task (IGT)(29). BPD patients were also observed to make riskier choices in a modified version of the IGT. Feedback-related negativity (FRN) data collected from the IGT indicated that those with BPD did not distinguish between positive and negative feedback. FRN measures also indicated greater impulsivity and risk-taking behavior in the BPD patients (30,31). Overall, BPD patients have been shown to be making impulsive choices with a bias towards more immediate gratification (32). Similarly, BPD patients' struggled to appropriately employ feedback from prior experiences when conducting the Game of Dice Task (33). Altogether, these findings suggest an impairment in the ability to appropriately weight different types of information – both in interpersonal but perhaps also in non-interpersonal decision-making scenarios. However, it is still unclear if BPD patients can appropriately learn and combine prior and likelihood information, particularly in a non-social decision-making scenario.

Here, we aim to further our understanding of BPD patients' decision-making behavior under a more general, non-social setting. In particular, we aim to assess BPD patients' use of and reliance on prior and likelihood information, a key lower-level building block of decision-making processes, within a generalized sensorimotor decision-making task in which the uncertainty of prior and likelihood information is modulated.

## Materials & Methods

### Participants

Eighteen BPD patients (15 women) and 23 neuro-typical adults (8 women) were recruited as participants. These participants were part of a larger study investigating decision-making in personality disorders (approved by the Research Ethics Committee for Wales). BPD patient referrals were obtained from psychiatrists or (trainee) clinical psychologists across London NHS Mental Health. The BPD diagnosis of each patient was confirmed through the Structured Clinical Interview for DSM-IV Axis II Diagnoses (34). Neuro-typical adults were recruited through online advertising. Participant exclusion criteria were diagnosis of a psychotic illness or recent psychotic episode, as well as any current substance use disorders or addictions from which they were not able to abstain on experiment days. History of neurological disorder(s) or traumatic brain injury also served as exclusion criteria. For controls specifically, existence of past or present mental disorder or personality disorder served as exclusion criteria. All participants were between 18 and 60 years of age and received a compensation of £10/hour for their time. Travel expenses were also reimbursed. Written informed consent was provided by all participants.

### Procedure/Task

To understand how the uncertainty of prior and likelihood information may influence decision-making, we employed a coin-catching sensorimotor task that modulated the uncertainty of both prior and likelihood information (13,20,35,36). We introduced the coin-catching task to the participants with a backstory involving an unknown person throwing a coin and aiming for the center of the pond. The task consisted of 600 trials, with 150 trials in each of the 4 blocks. However, for 3 of the 18 BPD patients, the number of trials were reduced to 480, with 120 trials in each of the 4 blocks, in order to accommodate for restlessness during the task. Following analyses, we found no difference in results between those who conducted 480 trials and those who conducted 600 trials. Participants were told that, during each block, a thrower throws a coin into the pond, and that the thrower changes between blocks (Figure 1). The coin's location in the pond is not shown, and participants were instructed to estimate this unknown location using the net. Every trial consisted of a visual display of the "pond", the splashes made by the coin thrown in, as well as the net. The pond spanned the entirety of a computer screen and was represented by a plain grey background with a random spread of several dark grey dots. The splashes were represented by a spread of 5 blue dots. The net was represented by a randomly placed blue bar spanning the vertical length of the display. Hence, only the x-axis was relevant for prediction of the coin's location. Participants were instructed to use the left and right arrow keys to move the net and to use the enter key to indicate where they think the coin may have landed (Figure 1A). Once they had indicated their placement of the net, the coin, represented by a yellow dot, was shown. They were also shown text indicating the current trial and their score, which is the number of trials that they have accurately estimated the location of the coin thus far (Figure 1B). This task was not timed. Unknown to the participants, we imposed two levels of uncertainty on both the prior and likelihood information such that we had 4 conditions (Figure 1C).

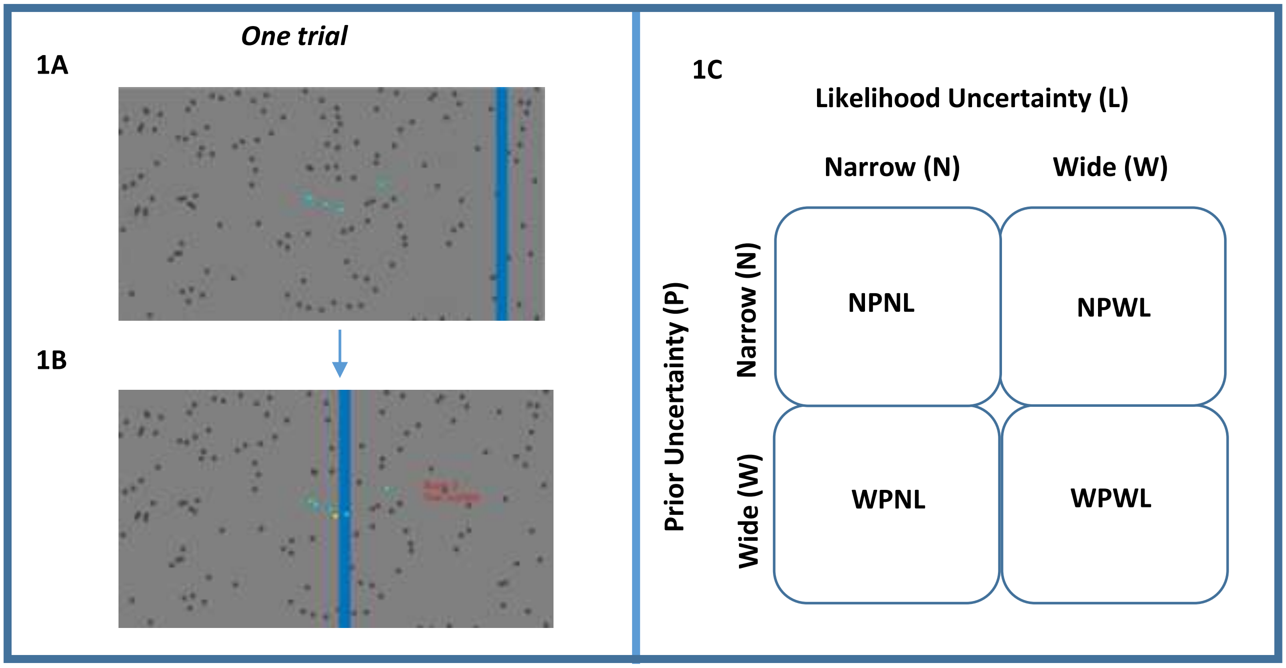


**Figure 1: (A)** When a trial begins, the display contains the net (net's initial placement is random), spread of several gray dots throughout the display, and spread of the 5 blue splashes. **(B)** The conclusion of a trial displays the true location of the coin along with the overall score in the task thus far and the number of the current trial. The red text displays the current score and the current trial number. **(C)** The 4 conditions are displayed above in terms of the level of uncertainty in the prior and likelihood information. Narrow distributions are associated with lower variance/more reliability, and wide distributions are associated with larger variance/more uncertainty. The 4 conditions and their abbreviations are: *NPNL* (narrow prior and likelihood); NPWL (narrow prior, wide likelihood); WPNL (wide prior, narrow likelihood), and WPWL (wide prior and likelihood).

The levels of uncertainty were experimentally defined as the variances of the prior and likelihood information. For each block, the coin position was taken from a Gaussian distribution (the prior distribution) where the mean was the center of the screen (0.5 in screen coordinates) and the variance was either narrow ($\sigma NP^2 = 0.025^2$) or wide ($\sigma WP^2 = 0.075^2$). Each prior condition was repeated two times (alternating), for a total of 4 blocks. While the transition between each block of the experiment represented a change in the variance of the prior information, the changes in the spread of the splashes along the x-axis from trial to trial explicitly displayed the changes in the variance of the likelihood information. The splashes that participants could see at each trial represent the likelihood and were obtained from a second Gaussian distribution where the mean was the coin position at that trial, and the variance, as depicted by the spread of the splashes, was either narrow ($\sigma NL^2 = 0.025^2 * 5$) or wide ($\sigma WL^2 = 0.075^2 * 5$). The spread of the splashes along the x-axis was counterbalanced with the spread along the y-axis. The likelihood variance varied pseudo-randomly across trials within a block, so that half of the trials used the narrow likelihood and half used the wide likelihood, but they could appear in any order. This way, the likelihood could not be predicted.

After the completion of the task, participants were asked to complete two more tasks designed to control for their performance. The first control task, which consisted of 100 trials, instructed participants to place the net on the visible coin. This task served as a way to measure performance to exclude those that did not complete the task as instructed (due to either a motoric or visual deficit, or inattention). The second control task, which also consisted of 100 trials, instructed participants to place the net at the mean location along the x-axis, or centroid, of the splashes. This task was used to assess how well participants were able to find the centroid (as the variance in likelihood changed). This control task's data was also used to calculate participants' subjective likelihood variances, which may differ from the experimentally imposed likelihood variances (see Supplementary Methods).

All participants completed this coin-catching task on a computer. Afterwards, participants completed a Borderline Personality Feature (PAI-BOR) self-report questionnaire (37) and the Barratt Impulsivity (BIS) questionnaire (38) in the convenience of their homes.

**Statistical Analysis**

See Supplementary Methods for details.

## Results

In order to quantify the use of priors and likelihoods, we utilized a linear regression model which used the centroid locations of the splashes and the locations of the placed net in the main task for each participant. The slope of the resulting simple linear regression model is called the sensory weight. We can interpret the value of the sensory weight as representing the level of reliance on likelihood information. A sensory weight of 1 would mean that the participant placed the net on the location of the centroid of the splashes on every trial, indicating that the participant relied completely on likelihood information throughout the task, regardless of the uncertainty of the information (solid line, Figure 2). On the other hand, a sensory weight of 0 would mean that the participant placed the net randomly in relation to the location of the centroid throughout the task (dashed line, Figure 2). This would indicate no reliance on likelihood information. If we assume the only information considered to make the decisions were priors and likelihoods, this could indicate complete reliance on prior information.

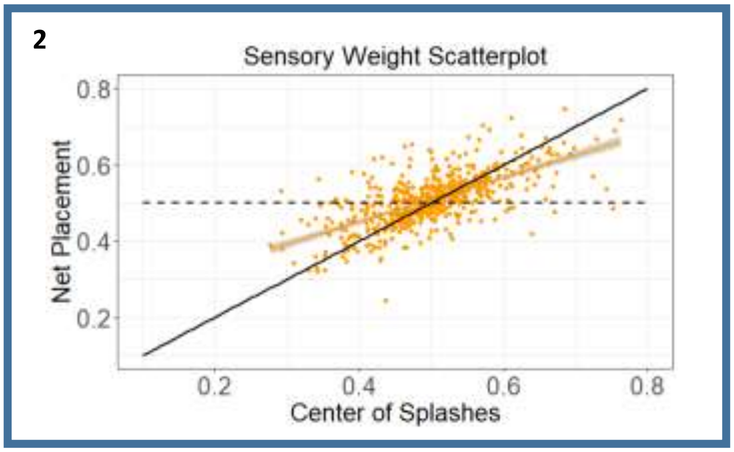


**Figure 2:** Sensory weight, for one example BPD patient participant. The x-axis indicates the center of splashes and the y-axis indicates the location of net placement of each trial. The orange data points represent trials from all 4 conditions of the coin-catching task for the example BPD patient participant, while the solid, orange line indicates the linear regression model for their data. The dashed line indicates an example of a sensory weight of 0. The solid, black line indicates an example of a sensory weight of 1. Both the x- and y-axis are displayed in screen units (representing the horizontal axis of the visual display).

### BPD patients were able to detect and respond to changes in uncertainty in priors and likelihoods

To assess BPD patients' ability to detect and respond to changes in the levels of uncertainty in both priors and likelihoods, we compared the difference in sensory weights between narrow uncertainty trials and wide uncertainty trials. To assess the main effect of the level of prior uncertainty, we gathered the sensory weights for the *narrow prior, narrow likelihood* (NPNL) and *narrow prior, wide likelihood* (NPWL) conditions and averaged them such that each patient had one average sensory weight for the NP condition. This procedure was followed to arrive at average sensory weights per patient within the WP condition as well. We found that the averaged sensory weights from the narrow prior uncertainty condition were significantly smaller relative to the ones from the wide prior uncertainty conditions ($t(22)$ = -3.259, $p$ = 3.597-03, *paired t-*

*test*; $M_{NP}$ = 0.556, $SD_{NP}$ = 0.058 vs. $M_{WP}$ = 0.688, $SD_{WP}$ = 0.044). Following a similar procedure, we found that a main effect also exists for the level of uncertainty in likelihood information ($t(22) = 8.953$, $p < .001$), where sensory weights from the narrow likelihood conditions were significantly higher compared with the wide (more uncertain) likelihood conditions ($M_{NL}$ = 0.706, $SD_{NL}$ = 0.045 vs. $M_{WL}$ = 0.538, $SD_{WL}$ = 0.052). In other words, BPD patients were sensitive to changes in both prior and likelihood information, which is reflected through significantly different sensory weight means between different uncertainty levels (Figure 3). Moreover, the difference followed what would be expected by Bayesian statistics: BPD patients relied more on likelihood information (i.e. had greater sensory weights) when the prior information was more uncertain (wide) or when the likelihood information was more reliable (see Figure 3).

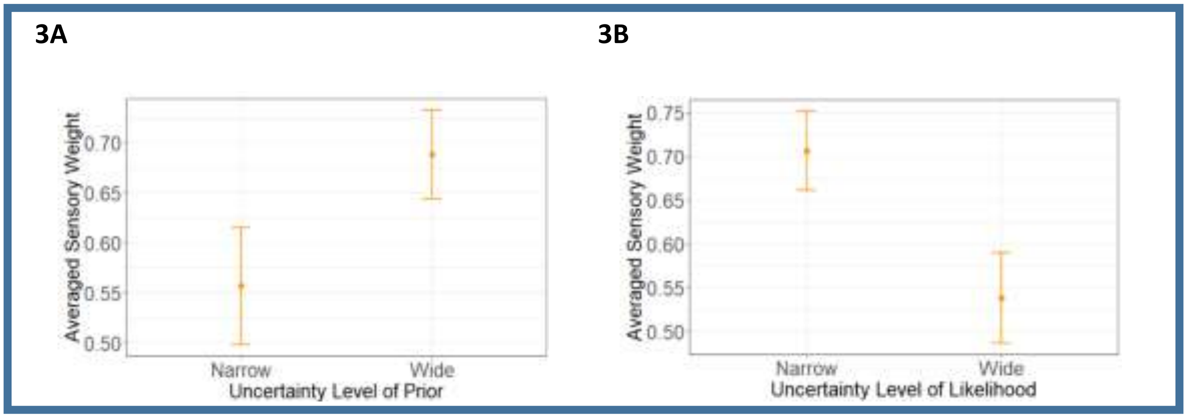


**Figure 3**: Significant main effects of uncertainty level were found for both **(A)** priors and **(B)** likelihoods in BPD patients, as reflected by average sensory weights and SEM. Sensory weights of patients were gathered according to level (narrow or wide) of uncertainty. Mean of sensory weights was $0.556 \pm 0.058$ when the uncertainty in prior information was narrow, and $0.688 \pm 0.044$ when the uncertainty in prior information was wide. Mean of sensory weights was $0.706 \pm 0.045$ when the uncertainty in likelihood information was narrow and $0.538 \pm 0.052$ when the uncertainty in likelihood information was wide. (See Supplementary Information for additional statistical results.)

### Relative usage and reliance on prior and likelihood information was not significantly different between BPD patients and controls

To understand how BPD patients and controls used prior and likelihood information and their respective uncertainties, we used a similar procedure as above to gather and average the appropriate sensory weights according to the uncertainty levels. First, we found that control participants also showed a main effect of prior and likelihood uncertainty (See Supplementary Information). Then, we looked at whether differences in sensory weights existed between BPD patients and controls (using 4 sensory weights per participant, corresponding to the 4 conditions; see Figure 1C and Figure 4). Through a repeated-measures analysis of variance (ANOVA) with prior, likelihood, and population (i.e., BPD patients or controls) as factors, we found a main effect for the level of uncertainty in the prior information ($F(1, 39) = 29.856$, p < .001), and a main effect for the level of uncertainty in the likelihood information ($F(1, 39) = 132.080$, p < .001). In other words, when patients and controls are grouped together, there still exists a main effect for the uncertainty level of prior information and for likelihood information for all participants as a whole. We also found an interaction effect between uncertainty levels of prior and likelihood information ($F(1, 39) = 6.978$, $p = .012$). However, we found no main effect for population ($F(1, 39) = 0.010$, $p = .921$). This indicates that, regardless of condition, sensory weights did not significantly differ between BPD patients and controls. There was also no interaction between uncertainty levels of prior and population ($F(1, 39) = 0.403$, $p = .529$), or between uncertainty levels of likelihood and population ($F(1, 39) = 0.291$, $p = .593$). Last but not least, there were no significant interaction effects between uncertainty levels of prior, uncertainty levels of likelihood, and population ($F(1, 39) = 3.367$, $p = .074$; see additional analyses in SI). These results indicate that both BPD patients and controls were able to detect changes in prior and likelihood uncertainty and respond accordingly, with no significant differences between the groups.

**BPD patients and Controls behaved qualitatively Bayesian-like, but not quantitatively**

We assessed whether BPD patients' behavior (and control participants' behavior) matched what is predicted by Bayesian Decision Theory. Succinctly put, this theory predicts that the information that has a lower level of uncertainty would be relied on more heavily than the information that has a greater level of uncertainty. Specifically, for this task, it predicted that the participants' sensory weights would be greater in the condition with narrow uncertainty in the likelihood information and wide prior uncertainty (this is our WPNL condition). Conversely, it predicted a participants' sensory weights would be smaller in the NPWL condition (see Figure 1C). In general, it predicts that participants would have higher sensory weights whenever the likelihood information is more reliable (less uncertain) and/or when the prior is more uncertain. Qualitatively, this is exactly what we observe (see Figure 4; see also Figure 3). To see if this happened not only at the group level but at the individual level, we used Bayes' rule to arrive at Bayesian estimations of the locations of the coin per trial and found that overall, both BPD patients' and controls' estimated coin locations significantly correlated with the Bayesian estimated locations of the coins (all BPD patients: $r$s > 0.375, $p$s < .001; all Controls: $r$s > 0.395, $p$s < .001; see SI). These results provided evidence for Bayesian-like behavior, for both BPD patients and controls, in deciding the locations of the coin throughout the task.

Next, we wanted to understand how participant behavior compared quantitatively to behavior as predicted by Bayesian Decision Theory. We found that BPD patients' sensory weights were significantly different from Bayesian-optimal sensory weights obtained using the experimentally-imposed variances ($t(22) = 2.561$, $p = .018$, one-sample t-test). Similarly, controls' sensory weights were also found to be significantly different from Bayesian-optimal sensory weights ($t(17) = 2.567$, $p = .020$, see SI for additional details and analyses). From these results, we could see that, quantitatively, both BPD patients' and controls' sensory weights were significantly different from Bayesian-optimal sensory weights. BPD patients' sensory weights were not significantly different from controls' sensory weights ($t(39) = 0.099$, $p = .921$) and thus likewise neither were they further from the optimal. These results indicate that both BPD patients' and control participants' use of prior and likelihood information differed quantitatively from what Bayesian-optimal behavior predicts, but that BPD patients were not further from the optimal compared to control participants.

These results were obtained using the experimentally-imposed variances, but these values may not necessarily be representative of participants' subjective experience of the uncertainty. Instead, we can calculate participants' subjective likelihood uncertainties using the data from the second control task (see Methods, SI, and Supp. Fig. 1 for details). We found that BPD patients' sensory weights were not significantly different from Bayesian-optimal sensory weights as calculated using subjective likelihood variances ($t(22) = -0.745$, $p = .464$). In other words, we did not find evidence of non-Bayesian behavior in BPD patients when the Bayesian-predicted sensory weights were calculated using subjective values for the likelihood variance. However, this may depend on the condition, with some obtained sensory weighs being above and others below the Bayesian optimal values (see Figure 4 and Supplementary Results). Similar results were found for controls ($t(17) = -2.085$, $p = .052$). The differences between participant sensory weights and the Bayesian-predicted sensory weights, as calculated using subjective likelihood variances, were not significantly different between BPD patients and controls ($t(39) = 0.793$, $p = .433$, see also SI). These results indicate that BPD patients' behavior may not necessarily be non-Bayesian when analyzed in a subjective context (although this depends on the condition), and is not further from the optimal compared to controls.

We also looked at BPD patients' task performance in comparison to responses to both the Borderline Personality Feature self-report questionnaire (PAI-BOR) and the Barratt Impulsivity questionnaire (BIS). We found no significant correlation between task performance and questionnaire scores (see SI).

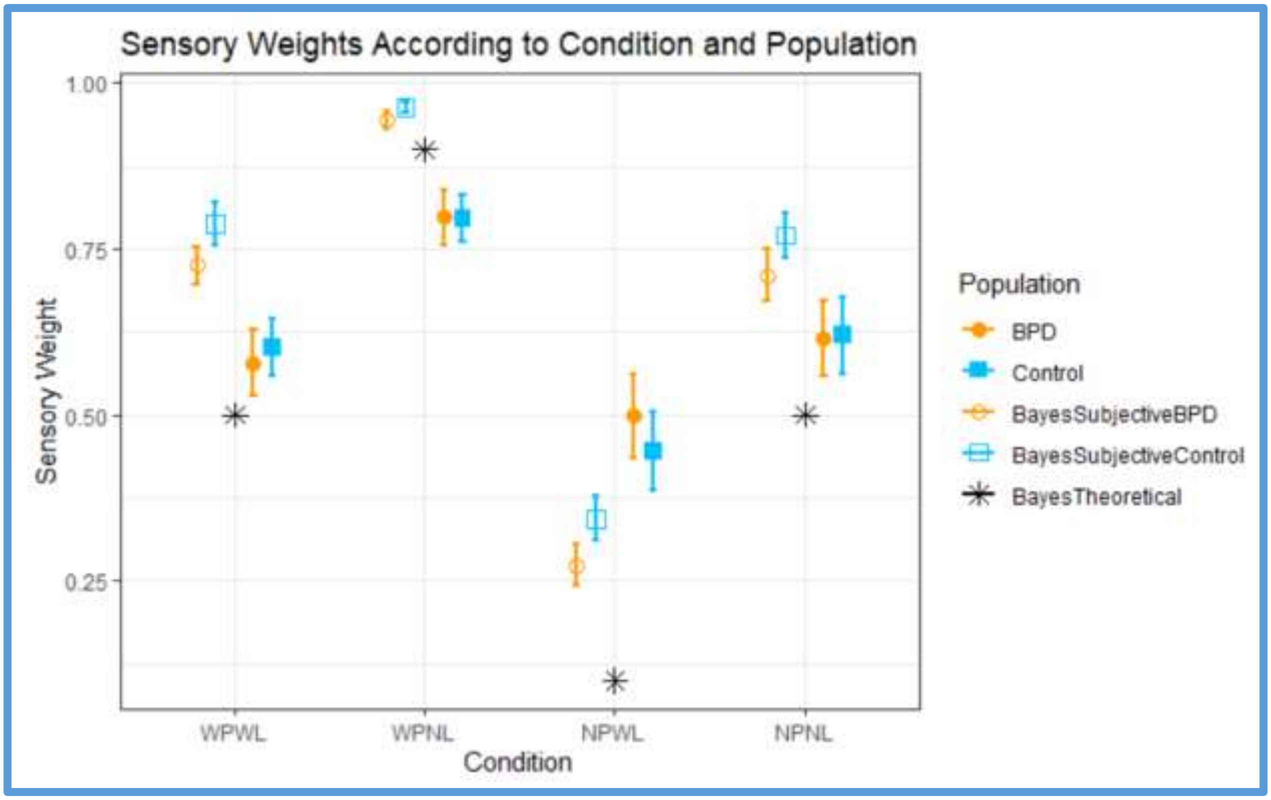


**Figure 4:** This figure displays the average sensory weights (and associated SEM) per condition and per population. The x-axis displays the conditions (see Figure 1C). The y-axis displays the range of sensory weights. The data depicted are grouped according to population type: BPD (patients), Control (participants), Bayesian-predicted sensory weights based on experimentally-imposed variances labeled as BayesTheoretical, and Bayesian-predicted sensory weights based on subjective likelihood variances labeled as BayesSubjectiveBPD and BayesSubjectiveControl.

## Discussion

In this study, we aimed to understand how those with BPD use prior and likelihood information to make decisions. Given certain typical characteristics of BPD such as impulsiveness, rapid changes in the perception of themselves and others, as well as sudden changes in mood and behavior, we hypothesized that this could stem from an overall low reliance in prior information and potential inability to use prior information appropriately, which may then translate into a greater reliance on likelihood information than prior information when making decisions. We found no significant difference in the weight given to current vs. prior information (sensory weights) between BPD patients and controls. We also found that BPD patients behaved in a manner qualitatively matching optimal behavior as predicted by Bayesian Decision Theory. Within the context of this particular sensori-motor paradigm, we found evidence in support of BPD patients' ability to distinguish, learn, and appropriately use both prior and likelihood information when making sensorimotor decisions.

We also hypothesized that those with BPD would not make decisions in a Bayesian-optimal manner. We found quantitative evidence in support of this hypothesis, but qualitatively, BPD patients' decision-making behavior was on par with Bayesian predictions. However, when we used the subjective variances instead of the experimentally-imposed variances, we found that they were not significantly different from optimal. In addition, BPD patients were not further from the optimal compared with controls. Thus, BPD patients' behavior could be at least qualitatively successfully captured by a Bayesian framework.

Overall, these findings suggest that in particular types of decision-making, such as within a purely sensorimotor decision-making paradigm, BPD patients' decision-making ability may not be impaired. Our results in support of qualitatively, but perhaps not quantitatively, Bayesian-like decision-making behavior in both BPD patients and neuro-typical adults are similar to prior studies' findings in neuro-typical adults (39,40).

However, the BPD results contrasted with results obtained in two recent studies (41,42). In these studies, BPD patients were presented with both a social and a nonsocial cue and were found to weigh sensory information differently from healthy controls (41,42). Namely, Fineberg and colleagues found that both social and nonsocial cues were more significantly weighted by BPD patients than the controls (41). This may suggest that those with BPD are more attentive to current sensory cues, or in other words, likelihood information. However, they also found blunted learning when there was higher reward volatility, in both social and non-social contexts, which would suggest that when there is higher reward volatility there is lower reliance on current information. Interestingly, while Henco et al. also found that BPD patients had slower learning rates from both social and non-social information, they found that BPD patients instead had an exaggerated sensitivity to changes in environmental volatility (42). In addition, both papers found that BPD patients responded more to social cues, and the differences that they found in learning rates between BPD patients and controls were more pronounced for the social cues (41,42). We believe that one of the main reasons for a difference among our results and theirs is the existence (or not) of a social component in the task. Due to the personal and social nature of this disorder, it is possible that decision-making paradigms involving a social component may aid in eliciting key characteristics of BPD and significantly affect BPD patients' ability to make decisions even in the non-social portions of the task. Our study is an important control experiment that provides evidence that differences observed by prior studies are not due to a generalized dysfunction in information processing but rather may be content related.

Our findings may have been limited by a small sample size. Future studies would benefit from replication using a larger pool of participants. In addition, these findings may not generalize to broader decision-making situations which may involve social components, particularly so in more affectively charged interpersonal situations where mentalizing one's counterpart requires emotion regulation and understanding of or inference of intentionality (24,43,44). A future direction of our current study could involve modifying the task to include different degrees of such social components, and see if and how behavior changes. We predict suboptimal use of prior information in these social contexts, especially if the social information comes from someone emotionally close to them. Nevertheless, our results indicate that any potential deficits in appropriately using priors in social contexts do not stem from a generalized inability to learn and use priors.

Our study provides evidence to support that BPD patients are able to learn both prior and likelihood information and their respective uncertainties and use it appropriately. Thus, our results challenge the notion that BPD patients have aberrant learning irrespective of the domain (42), and indicate that, at least within the context of sensorimotor decision-making, BPD patients are able to learn and make decisions appropriately in a way that is predicted by Bayesian Decision Theory.

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**Data Availability**

Data will be made publicly available on the Open Science Framework (https://osf.io/).

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