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FULL-LENGTH REPORT

Learning and metacognition under volatility in GD: Lower learning rates and distorted coupling between action and confidence

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ABSTRACT

Background and aims: Decisions and learning processes are under metacognitive control, where confidence in one's actions guides future behaviour. Indeed, studies have shown that being more confident results in less action updating and learning, and vice versa. This coupling between action and confidence can be disrupted, as has been found in individuals with high compulsivity symptoms. Patients with Gambling Disorder (GD) have been shown to exhibit both higher confidence and deficits in learning. *Methods:* In this study, we tested the hypotheses that patients with GD display increased confidence, reduced action updating and lower learning rates. Additionally, we investigated whether the action-confidence coupling was distorted in patients with GD. To address this, 27 patients with GD and 30 control participants performed a predictive inference task designed to assess action and confidence dynamics during learning under volatility. Action-updating, confidence and their coupling were assessed and computational modeling estimated parameters for learning rates, error sensitivity, and sensitivity to environmental changes. *Results:* Contrary to our expectations, results revealed no significant group differences in action updating or confidence levels. Nevertheless, GD patients exhibited a weakened coupling between confidence and action, as well as lower learning rates. *Discussion and conclusions:* This suggests that patients with GD may underutilize confidence when steering future behavioral choices. Ultimately, these findings point to a disruption of metacognitive control in GD, without a general overconfidence bias in neutral, non-incentivized volatile learning contexts.

KEYWORDS

gambling disorder, metacognition, confidence, learning, volatility

INTRODUCTION

Gambling Disorder (GD) is a recognized psychiatric disorder characterized by a loss of control and an inability to stop gambling despite known adverse consequences (American Psychiatric Association, 2022; World Health Organization, 2022). This behavior has spurred numerous studies to investigate the decision-making processes underlying this behavior, including reinforcement learning.

Learning in GD has frequently been investigated by feedback-based learning tasks, such as reinforcement learning, reversal learning and model-based learning, revealing various impairments. Using reinforcement learning tasks, patients with GD have shown to have less strategic exploration of choice options, lower non-decision time, more decision noise, and lower learning rates for losses, but higher learning rates for rewards (for a review, see (Hales, Clark, & Winstanley, 2023)). There is also evidence of impairments in probabilistic reversal

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learning (Boog et al., 2014; de Ruiter et al., 2009; Perandrés-Gómez, Navas, van Timmeren, & Perales, 2021; van Timmeren, Daams, van Holst, & Goudriaan, 2018). Studies focusing on model-based learning have also suggested that patients with GD rely more on model-free than model-based learning than control participants (Bruder, Wagner, Mathar, & Peters, 2021; Wyckmans et al., 2019), however not all studies showed this (Van Timmeren, Van Holst, & Goudriaan, 2023; Wagner, Mathar, & Peters, 2022). In all, there is evidence that GD is associated with deficits in (reinforcement) learning and decision-making.

Decision-making and learning processes are guided by metacognitive control, a process rooted in metacognition – our capacity to monitor and reflect upon our thoughts and actions. This capacity can be assessed by prompting individuals to evaluate their level of confidence in the accuracy of their choices. Indeed, research has demonstrated that confidence has a guiding role in information seeking, impacting decision-making, reassessment of choices, and learning (Balsdon, Wyart, & Mamassian, 2020; Desender, Boldt, & Yeung, 2018; Meyniel, Schlunegger, & Dehaene, 2015). Moreover, confidence contributes to the adaptable adjustment of behavior, influencing the balance between exploration and exploitation (Boldt, Blundell, & De Martino, 2019; Heilbron & Meyniel, 2019). Thus, a sense of confidence about one's choices has been demonstrated to be indispensable for optimal decision-making.

An influential Bayesian framework of learning shows that confidence in actions influences behavior (Knill & Pouget, 2004; Meyniel, Sigman, & Mainen, 2015; Parr & Friston, 2017). Crucially, this framework predicts that the impact of new information on subsequent actions depends on the epistemic confidence of the decision-maker. When one is more confident, new information has less impact, resulting in less action updating and less learning. Conversely, lower confidence motivates gathering additional evidence to increase confidence in possible actions and also facilitates learning. Thus, in healthy populations, there is a strong link between confidence and subsequent action and learning. However, in many psychiatric disorders, confidence judgments are distorted, showing underconfidence or overconfidence relative to performance (Hoven et al., 2019). Specifically, patients with GD have exhibited overconfidence, particularly in contexts involving monetary gains (Goodie, 2005; Hoven et al., 2022). Studies investigating the coupling between confidence and action, and their relationship with psychiatric symptoms have shown that individuals with high compulsive (but not gambling) symptoms have a weakened confidence-action coupling (Seow & Gillan, 2020). This suggests that highly compulsive individuals tend to consider their confidence to a lesser extent when informing their future actions. However, it is currently unknown whether the relationship between confidence and action, and subsequent learning, is affected in GD.

Based on earlier findings, we hypothesized that patients with GD, relative to control participants, show higher confidence, less action-updating and lower learning rates. With regard to the coupling of confidence and subsequent actions, we posited two hypotheses. First, patients with GD could have an intact coupling between confidence and action, in line with the Bayesian framework. The alternative hypothesis posited that GD patients (similar to findings of individuals with highly compulsive symptoms) have a weakened confidence-action coupling.

To test these hypotheses, we investigated confidence, action, their coupling and learning by using a predictive inference task originally described by (Nassar, Wilson, Heasly, & Gold, 2010), and used in many studies since (Hoven, Mulder, Denys, van Holst, & Luigjes, 2023; Seow & Gillan, 2020; Vaghi et al., 2017) in patients with GD and matched control participants. Our results revealed that patients with GD have a weaker action-confidence coupling but exhibit similar confidence levels and action updating compared to control participants. Moreover, patients demonstrated lower learning rates than control participants.

METHODS

Participants

27 (4 women) patients with GD and 30 (6 women) healthy control participants (HCs) were included in this study, matched on age, sex and education. Patients with GD were recruited through patient clinics in the Netherlands and HCs via an online participation pool. All patients with GD had been in treatment for their gambling problems at least once and had gambled regularly within the past 12 months prior to participating. Information about the onset of GD and gambling game preference were not assessed. The HCs did not currently or in the 6 months prior to participation suffer from any psychiatric disorders and did not use any psychotropic medication. No a-priori power analysis was performed, as our sample size was based on earlier clinical studies using the same paradigm in OCD (Vaghi et al., 2017).

Experimental procedure

Predictive inference task. All participants performed a predictive inference task, similar to the one reported in (Vaghi et al., 2017), implemented using Psychtoolbox in MATLAB.

This task allows for the investigation of the relationship between error-driven learning and confidence, by letting participants infer the landing location of a particle based on its previous landing locations. A circle with a dot in the center was shown to participants, after which they had to place a "bucket" (represented by a curved rectangle) at the location at which they predicted a particle (i.e. a 'coin') would land. The position of the bucket could be updated every trial in response to new information. After confirming the location of the bucket, participants were asked to rate their confidence that they would catch the particle in the bucket on a scale of 1 (not at all confident) to 100 (extremely confident) (Fig. 1).

After the confidence rating was confirmed, the particle would fly from the center dot to the edge of the circle.

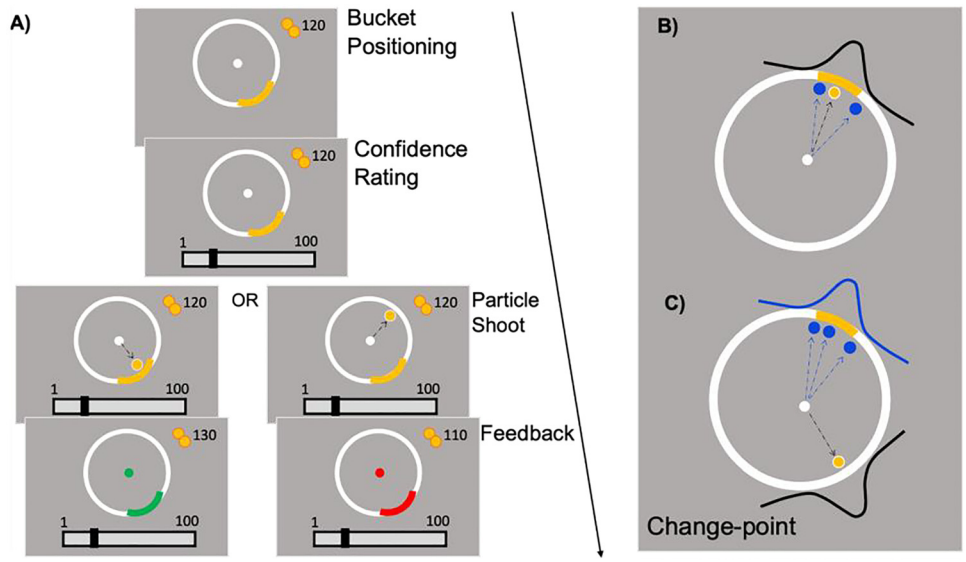

Fig. 1. **Predictive Inference Task. (A)** Trial of the predictive inference task. Participants positioned their bucket (i.e. yellow bar) to catch a flying particle that was released from the center dot to the edge of the circle. After positioning their bucket, participants indicated their confidence in catching the particle. The particle was either caught (bar turned green) or missed (bar turned red), which resulted in gaining or losing points, respectively. The number of points obtained is shown in the right upper corner. **(B)** In every trial, the landing positions of the particles were sampled from a random Gaussian distribution with a standard deviation. This noise resulted in the particles to land close together with a small amount of noise. Current trial particle trajectory is marked in black, while previous trials particle trajectories are marked in blue. Over time participants learn about the Gaussian distribution from which the particle trajectories are drawn. **(C)** During a change-point the mean of the Gaussian distribution of the landing position changes. After a change point, the landing positions are again sampled using the new Gaussian distribution, until a new change-point occurs. Figure was adapted with permission from Seow et al. (2020)

The landing location of the particle was sampled from a Gaussian distribution with a fixed standard deviation (SD) of 12. At certain 'change-point' (CP) trials a new mean for the particle landing location was drawn from a uniform distribution over the full range of the circle U(1,360), with a fixed probability of 0.125 (hazard rate, H). Performing accurately on this task thus required participants to distinguish between actual signals of change (i.e. CP trials) and noise (SD of the generative Gaussian distribution). When the particle landed in the bucket, participants received points, and they were penalized for missing the particle.

The task consisted of 4 blocks of 75 trials, with a practice round that was not included in the analyses. Participants were instructed to earn as many points as possible, which would be converted to a bonus up to €5. Confidence ratings were not directly incentivized, but participants were instructed to rate their confidence as accurately as possible.

Moreover, a subset of the sample (24 GD, 15 HC) additionally performed the predictive inference task at a higher hazard rate of 0.20, corresponding to higher task volatility. As the main focus of this paper is on the results of the original task, analyses pertaining to the higher volatility task can be found in the Supplementary Materials.

Task-based exclusions

Based on exclusion criteria set by (Seow & Gillan, 2020) and our previous study using this task (Hoven, Mulder, et al., 2023), we excluded participants when their mean confidence after hits was lower than their mean confidence after misses ($n = 6$, of which 2 GD). Since this current version of the task (lab-based instead of online (Seow & Gillan, 2020)) did not randomly initialize the confidence rating every trial, we cannot use previously used exclusion criteria pertaining to the deviation of participants' confidence ratings compared to the initialized confidence rating. After applying the subject-based exclusion criteria, the final dataset included data from 51 participants (25 GD (4 females), 26 HC (6 females)). For one participants with GD, data for one out of four blocks was corrupted and thus this subject has data for 225 instead of 300 trials. Since previous studies did not use any exclusion criteria based on accuracy on the task, here we also did not apply accuracy-based exclusion criteria. However, when inspecting the data, one participant with GD showed an average accuracy of around 18%, and analyses excluding this subject are detailed in the Supplementary Materials. In addition to subject-based exclusions, we also performed trial-based exclusions (see section '*Computational Model*').

Analyses

All data analyses were conducted using MATLAB (version 2018b) and R (version 4.2.1) using packages lme4, lmerTest, nlme and emmeans (Bates, Mächler, Bolker, & Walker, 2015; Kuznetsova, Brockhoff, & Christensen, 2017; Lenth, Singmann, Love, Buerkner, & Herve, 2018; Pinheiro, Bates, & R Core Team, 2022), and were similar to our previous case-control work in OCD for consistency (Hoven, Mulder, et al., 2023).

Action and confidence. First, to compare action updating and confidence between groups, separate linear-mixed effects models were fitted with either action update (absolute difference in bucket position from trial (t) to trial (t+1)) or confidence as dependent variable and a fixed effect of group, together with random intercepts per subject.

Action-confidence coupling. Second, differences in the strength of action-confidence coupling between groups were assessed using a mixed-effects model with action update as the dependent variable and confidence (z-scored), group and their interaction as fixed effects together with random intercepts and random slopes of confidence per subject.

In addition, we conducted two Pearson's correlation tests to examine the relationship between the strength of action-confidence coupling (using subject-level β coefficients of the action-confidence coupling model) and PGSI and GBQ scores in the GD group.

Computational model. Third, a computational approach was employed, similar to earlier work (Hoven, Mulder, et al., 2023; Marzuki et al., 2022; Seow & Gillan, 2020; Vaghi et al., 2017), in order to examine whether and how the relationship between behavior on the task (i.e. action or confidence) and various parameters describing the volatile environment differed between groups. In a volatile setting, where the environment is subject to frequent changes, participants need to adjust their learning rate based on recent information to update their beliefs about the generative distribution. When significant discrepancies between predicted and observed outcomes occur (i.e., large prediction errors), indicating a substantial shift in the environment, belief updates need to be strong and learning rates should be higher. Conversely, when prediction errors are small and likely due to random fluctuations, belief updates are less necessary, resulting in lower learning rates.

For each trial, the human prediction error $\widehat{\delta}_t$ (PE) was calculated as the difference between the current bucket position b_t and the particle landing location X_t .

$$\widehat{\delta}_t = X_t - b_t$$

Subsequently, the human learning rate $\widehat{\alpha}_t$ (LR) was calculated as the proportion of PE used for the subsequent action update, which was calculated as the absolute difference in bucket position from trial (t) to trial (t+1):

$$\widehat{\alpha}_t = \frac{|b_{t+1} - b_t|}{\widehat{\delta}_t}$$

Following earlier studies, trials were excluded from all analyses if the LR exceeded the 99th percentile which was calculated separately for each group (Seow & Gillan, 2020; Vaghi et al., 2017). In addition, trials where PE = 0 were excluded, since these trials do not drive error-driven learning (1.95% of GD trials, 1.97% of HC trials). Additionally, the first and last trials within each block were excluded from analyses; in the first trials, there is no error-driven learning yet, and for the last trials no learning rate could be calculated. In total, 5.49% of GD trials and 5.52% of HC trials were excluded from analyses.

Error sensitivity. To assess group differences in error sensitivity in terms of learning, a linear mixed model with human LR as the dependent variable and human PE, group and their interaction as predictors was run. For visualization purposes, PE was binned into 20 quantiles with each an equal fraction of trials, for which the average LR was computed per subject.

Bayesian observer model analyses. Following previous research (Marzuki et al., 2022; Seow & Gillan, 2020; Vaghi et al., 2017), behavior of participants was analyzed using a quasi-optimal Bayesian observer model that approximates optimal task behavior (Nassar et al., 2010). Using the model code that is publicly available (Vaghi et al., 2017), we fitted the particle landing locations of all participants to obtain individual-level model parameters. These parameters represent various statistical characteristics of the environment experienced by participants during the task. They include, on a trial-by-trial basis, the prediction error δ (PE, the absolute difference between model belief and location of the coin), the probability that a change-point occurred (CPP, the likelihood that the sampling distribution of the coin's location has changed, thus that a change-point has occurred), and relative uncertainty (RU, the fraction of uncertainty about the generative mean that is not due to noise). RU was expressed as its inverse, termed model confidence (MC, the precision of the model's beliefs about the mean), to allow for a more direct comparison with confidence judgments from the task. For more detail on the model see supplementary materials.

After fitting the model to the task data and obtaining the latent parameters for each subject, we assessed how these parameters related to participant behavior (action and confidence), and whether these relationships differed between the groups. Following previous studies, two separate mixed-effects models were assessed, where participant behavior (either action or confidence) was regressed against three model parameters: absolute PE, CPP and (1-CPP) (1-MC), and the categorical variable hit, indicating whether the particle was caught or not. Here, PE represents information regarding the most recent observation, while CPP and (1-CPP) (1-MC) represent the model's estimation that a change-point did or did not occur, given the sequence of past observations, respectively. For the action model, the dependent variable was calculated as: LR * PE, which is equal to the bucket update, and the predictors were also interacted with PE, following previous work (McGuire, Nassar, Gold, & Kable, 2014; Nassar, McGuire, Ritz, & Kable, 2019; Seow & Gillan, 2020; Vaghi et al., 2017). For both models, all fixed-effects were z-scored and interacted with group. Random intercepts and slopes of all predictors were also included in the models.

In the Bayesian model, the hazard rate is a constant of 0.125, which is equal to the hazard rate in the task. As additional sensitivity analyses we furthermore calculated the perceived hazard rate as a free parameter for each subject

based on the best fit of the model on the participant's behavior (see Supplementary Material for more information).

Ethics

The study was approved by the Ethics Board of the Behavioral Science Laboratory at the University of Amsterdam (2018-DP-9420). All participants provided written informed consent and were reimbursed for their time.

RESULTS

There were no differences in age ($t_{49} = 0.42$, $p = 0.68$), gender distribution ($X^2 = 0.40$, $p = 0.52$) or education level ($t_{49} = -0.38$, $p = 0.71$) between HC and GD groups. For details on demographics, clinical and task data, see Table 1.

No group differences in action updating or confidence

Mixed-model analyses were conducted to test group differences in task behavior (i.e. action and confidence). No differences in the amount of action updating ($\beta = -1.02$ (1.24), $t = -1.82$, $p = 0.415$, group difference = 1.03 degrees of bucket placement), nor differences in confidence ($\beta = -2.67$ (6.54), $t = -0.41$, $p = 0.684$, group difference = 2.68) were found between groups (Table 1, Fig. 2). Accuracy was equal between the groups as well ($t_{49} = -0.95$, $p = 0.345$, group difference = 2.11 percent accuracy). The proportion of trials in which no action update was performed was higher in GD, however ($t_{49} = 2.48$, $p = 0.017$; GD = 60.1%, HC = 50.5%).

Weaker action-confidence coupling in GD

Next, we evaluated whether the coupling between action update and confidence differed between the groups. As expected, a significant negative relationship between confidence and action update existed across groups, such that higher confidence was related to less action updating (i.e. action-confidence coupling) ($\beta = -8.26$ (1.14), $t = -7.23$, $p < 0.001$). Moreover, there was evidence for a distortion of this action-confidence coupling in GD, as a significant interaction between group and confidence was found ($\beta = 3.28$ (1.63), $t = 2.01$, $p = 0.045$), indicating a weaker action-confidence coupling in GD (estimated marginal slope = −4.98 (1.17)) than in HC (estimated marginal slope = −8.26 (1.14)) (Figure 2).

Within the GD group, no significant correlation was found between action-confidence coupling and PGSI score ($r = -0.23$, $p = 0.266$), or GBQ score ($r = -0.07$, $p = 0.754$).

Table 1. **Demographic, clinical and task variables**. Abbreviations: GD = Gambling Disorder, HC = Healthy Controls, PGSI: Problem Gambling Severity Index, GBQ: Gamblers Belief Questionnaire. Data are reported as mean (standard deviation)

	Participants with GD	HC participants
Age	36.8 (11.4)	35.6 (8.8)
Females (%)	4 (16.0%)	6 (23.1%)
Education Level	3.12 (0.9)	3.23 (1.2)
PGSI	15.1 (4.2)	
GBQ	56.4 (21.2)	
Accuracy (%)	60.17 (9.78)	62.28 (5.46)
Confidence	47.84 (25.16)	50.52 (21.45)
Confidence Update	15.12 (8.62)	13.35 (7.40)
Learning Rate	0.37 (0.14)	0.47 (0.21)
Action Update	18.59 (4.31)	19.62 (4.57)
Prediction Error	27.22 (10.99)	24.61 (2.29)

Lower learning rates in GD

We also assessed differences in learning rates and the error sensitivity in terms of learning between the GD and HC groups. Across both groups, learning rates increased as a function of prediction error magnitude ($\beta = 0.006$ (0.0002), $t = 39.51$, $p < 0.001$), and thus learning rates were highest after large errors. Moreover, learning rates were found to be significantly lower overall in the GD group ($\beta = -0.13$ (0.05), $t = -2.39$, $p = 0.021$, group difference = 0.10), but no evidence was found for an interaction effect between PE and group (Fig. 3).

To look at the group differences in cases of low, middle or high error magnitude, following previous research (Hoven, Mulder, et al., 2023; Vaghi et al., 2017), a mixed-model analysis binning the prediction error in 3 quantiles (i.e., low, medium or high error magnitude) was run. This indicated that patients with GD specifically had decreased learning rates when error magnitude was small (HC-GD estimate = 0.13 (0.05), Z-ratio: 2.60, $p = 0.009$) and medium (HC-GD estimate = 0.19 (0.05), Z-ratio: 3.79, $p < 0.001$). This indicates that when errors were of small or medium size, the influence of the most recent outcome on subsequent action (i.e. PE) was lower in the GD compared to the HC group, whilst this did not differ for larger PEs.

Stronger effect of uncertainty about the generative mean of the distribution on action in GD

Finally, we assessed whether task behavior (action and confidence) was differently predicted by the latent model parameters that represent different forms of uncertainty and feedback in the volatile environment. As expected, action was significantly predicted by all model-derived parameters and hit, such that increases in PE, CPP and (1-CPP)*(1-MC) predicted an increase in action, while a successful catch of the particle predicted a decrease in action. Moreover, a significant interaction between group and the (1-CPP)*(1-MC) parameter indicated a stronger effect of relative uncertainty of the belief about the mean of the distribution in the GD group (estimated marginal slope = 3.81 (0.52)) compared to the HC group (estimated marginal slope = 2.09 (0.51)) ($\beta = 1.72$ (0.72), $t = 2.37$, $p = 0.022$) (Fig. 4).

Confidence was, as expected, significantly negatively predicted by CPP and (1-CPP)*(1-MC), but only marginally by PE, and significantly increased with a successful catch of the particle. We did not find any evidence for group differences in the strength of these effects (see Supplementary Materials).

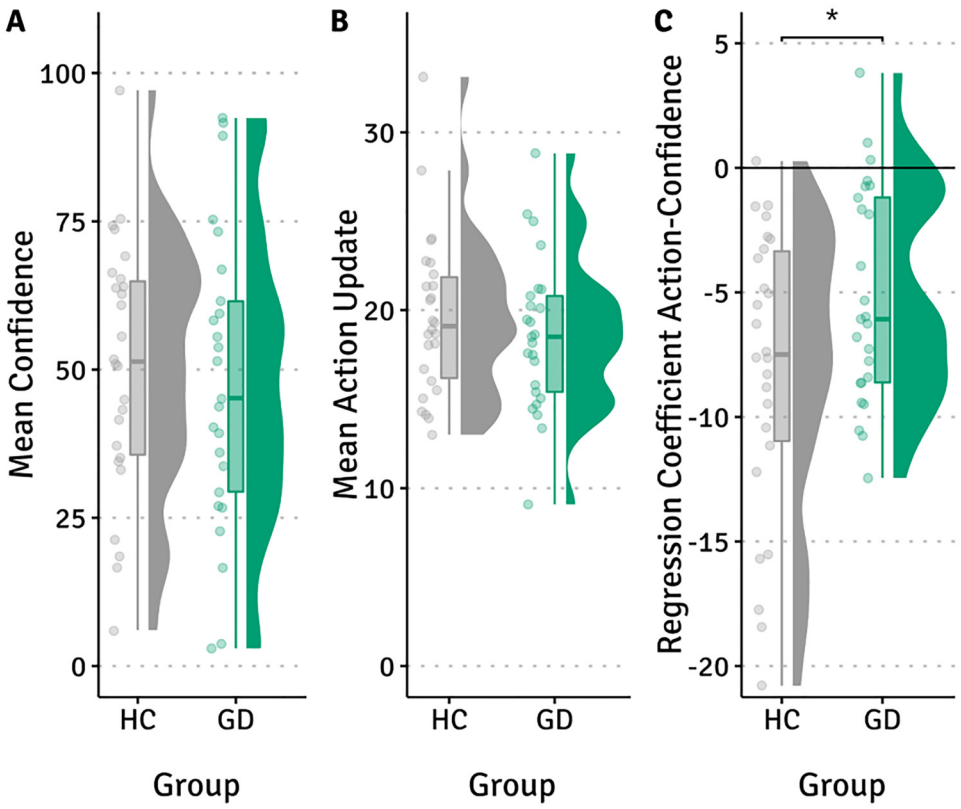

Fig. 2. **Task behavior across groups.** Mean confidence **(A)** and action update **(B)** per group. **(C)** Regression coefficient from the relationship between action update and confidence. As expected, regression coefficients were negative indicating that lower confidence was associated with bigger action updates of the location of the bucket. Dots represent **(A) (B)** data from individual participants and **(C)** regression coefficients of individual participants. Boxplots show median and upper/lower quantile with whiskers indicating the 1.5 interquartile range, distributions show the probability density function of all data points per group. Significance stars represent the main effects of group in the respective mixed-effects models. $^{*}p < 0.05$, $^{**}p < 0$ .01, $^{***}p < 0.001$. HC = healthy control participants, GD = patients with gambling disorder

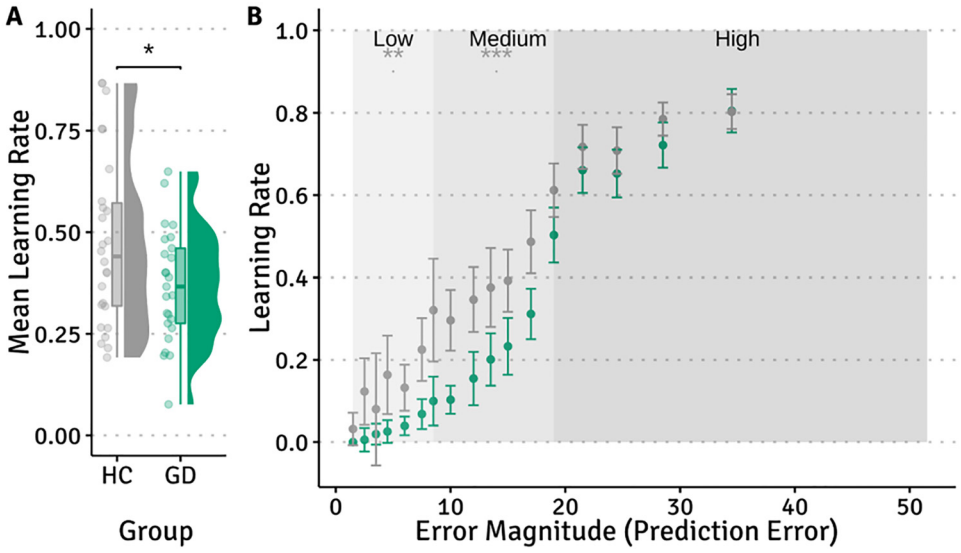

Fig. 3. **Learning rates and error sensitivity. (A)** Mean learning rates per group ($\widehat{\alpha}_t$). Patients had significantly decreased learning rates compared to the HC group. Dots represent learning rates of individual participants, boxplots show median and upper/lower quantile with whiskers indicating the 1.5 interquartile range, distributions show the probability density function of all data points per group. **(B)** The relationship between prediction error magnitude ($\widehat{\delta}_t$) and learning rate for both group. Prediction errors were divided in 20 quantiles, of which 18 quantiles are shown here for visualization purposes. Dots represent mean learning rates per group, error bars represent the SEM. Overall, learning rates were higher when prediction errors were larger. Learning rates were lower in the GD group compared to the HC group at low and medium error magnitudes. $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

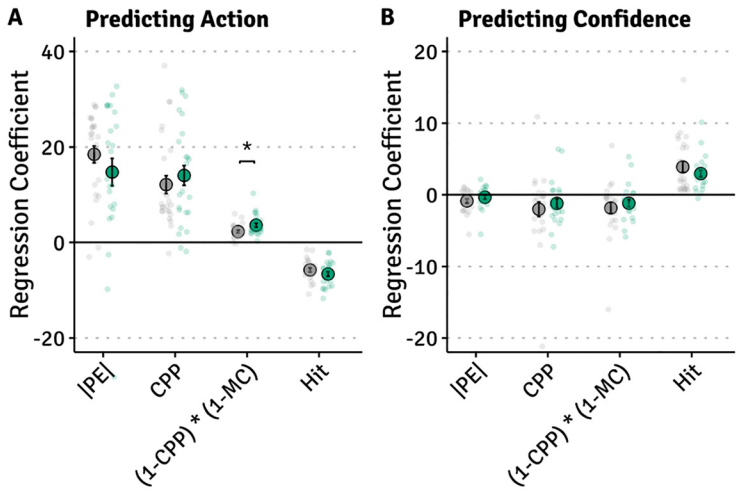

Fig. 4. **Model-based results on action and confidence.** Regression coefficients of the regressions assessing the relationship between the parameters from the computational model and **(A)** human action (i.e. learning rate * absolute prediction error), or **(B)** human confidence. Small dots represent individual regression coefficients, big dots represent mean regression coefficients per group, error bars denote SEM per group. Predictors included absolute prediction error (PE), change-point probability (CPP), model confidence (MC) and a categorical variable representing hits/misses. $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

No group differences in perceived hazard rates

Sensitivity analyses using the subject-specific perceived hazard rate (see Supplementary Materials) first of all showed no differences in hazard rate between groups (mean GD: 0.54, mean HC: 0.59: $t_{49} = -0.61$, $p = 0.542$). Moreover, in sensitivity analyses we performed the same analyses as described above, but including the subject-specific hazard rate as a covariate. These analyses indicated that none of the significant group differences that were found were influenced by differences in perceived hazard rate. For more details, see Supplementary Materials.

DISCUSSION

Drawing on previous observations of increased confidence and impaired reinforcement learning in GD, here we extended the literature by investigating the connection between confidence and action updating and subsequent learning in patients with GD. Our results showed that patients with GD demonstrated comparable levels of confidence, action updating, and performance, but had a weaker coupling between confidence and action. This indicates that patients with GD assign less significance to their confidence levels when performing actions under volatility. These findings support the hypothesis that GD is characterized by decreased confidence-action coupling.

This dissociation between action and confidence resembles the clinical presentation of GD, where patients often continue gambling despite knowing it is unwise. It suggests a disruption in metacognitive control, which might also be associated with a disruption of model-based action (Voon et al., 2015), as has been found in GD before (Bruder et al., 2021; Wyckmans et al., 2019). Though current models for gambling behaviour do not incorporate the role of metacognition or confidence, we can draw on a recent model of obsessive-compulsive disorder (OCD) (Fradkin, Adams, Parr, Roiser, & Huppert, 2020). This model describes that compulsive behavior can arise from overreliance on prior beliefs (e.g., overconfidence in those beliefs) at the expense of new evidence, leading to less learning, more stickiness, and habitual behaviour. This kind of behaviour was indeed observed in highly compulsive individuals from the general population, indicating lower learning rates and decreased action-confidence coupling (Seow & Gillan, 2020), although gambling symptoms were not explicitly assessed in this study. The current metacognition findings in GD can be contextualized within two leading models: the pathway model (Nower, Blaszczynski, & Anthony, 2022) and the I-PACE model (Brand et al., 2019). The pathway model outlines three unique gambling pathways with specific risk factors but lacks detail on (neuro) cognitive processes, a gap filled by the I-PACE model. This model illustrates the interplay between personal traits (like genetics and early experiences) and predisposing behavioral factors (needs, incentives, values), shaping responses to triggers and influencing behavior through cognitive and affective processes. Our suggestion is to further enrich the I-PACE model by integrating metacognition to better understand (and potentially impact) decision-making processes in GD.

The current findings indicate overall lower learning rates in GD, with a specific decrease in learning rates when the error magnitude was small or medium. GD patients overall seem to move their bucket position less frequently (i.e., significantly lower proportion of trials in which the bucket was moved), while there was no difference in the degree of movement (i.e., action update). This suggests that patients exhibit more sticky behaviour than control participants,

which aligns with prior research (Perandrés-Gómez et al., 2021; van Timmeren et al., 2018; Wiehler, Chakroun, & Peters, 2021). However, lower learning rates in GD were not always directly evident in experimental tasks (Hales et al., 2023). For example, a recent study employing a probabilistic instrumental learning task with three conditions (reward, avoidance, neutral) found no overall differences in the proportion of correct choices between patients with GD and HCs in reward or avoidance trials. However, employing a computational model with two separate learning rates revealed that patients with GD exhibited relatively excessive sensitivity to positive prediction errors (PEs), but insensitivity to negative PEs (Suzuki et al., 2023). These findings underscore the notion that GD might be linked to subtle and specific differences in learning rates, which might not always be easily discernible without employing sensitive experiments and computational modeling (Hales et al., 2023).

Our study found no evidence of increased confidence judgements in patients with GD, a finding that aligns with previous research using a non-incentivized learning task (Brevers et al., 2014). This contrasts, however, with studies that have used monetary incentives, where GD patients have shown higher levels of confidence (Goodie, 2005; Hoven et al., 2022). As suggested (Hoven, Hirmas, Engelmann, & Holst, 2023), it appears that overconfidence in GD manifests mainly in disorder-relevant contexts, such as during gambling task or when gains or risk are involved. This raises important questions for future research: under what circumstances do distortions in confidence occur in GD, and how do these distortions impact learning and decision-making?

Recent investigations in healthy populations have begun to elucidate the relationship between learning biases and confidence biases (Lebreton, Bacily, Palminteri, & Engelmann, 2019; Salem-Garcia, Palminteri, & Lebreton, 2023; Ting, Salem-Garcia, Palminteri, & Engelmann, 2023). These studies have shown that individuals tend to be more confident when learning to seek gains as opposed to avoiding losses. This 'valence-induced confidence bias' has been linked to reduced context-dependent learning, while a general overconfidence bias correlated with a confirmatory learning bias (Salem-Garcia et al., 2023; Ting et al., 2023). Applying this framework to GD, one could hypothesize that in an incentivized reinforcement learning task, GD patients would exhibit both elevated confidence and a more pronounced valence-induced confidence bias. This in turn could be associated with increased confirmatory learning and decreased context-dependent learning relative to HCs. This pattern could offer insights into rigid, disadvantageous decision-making in GD. Subsequent research should validate these hypotheses, potentially providing a more nuanced understanding of the cognitive biases at play in GD.

Our current study comes with limitations. In line with prior research, we integrated model-based analyses for consistency. However, it's important to note that while recent findings suggested good internal consistency and test-retest reliability for the main measures of confidence and learning rate, the psychometric quality of the Bayesian model parameters was comparatively lower (Loosen, Seow, & Hauser, 2023). This implies that the utilization and interpretation of model-based metrics should be exercised cautiously, particularly when examining differences between individuals. Also, the predictive inference task does not resemble a real-world gambling game. Hence, enhancing the ecological validity of our approach could involve using a task that simulates monetary involvement and enforces penalties for excessive action updating. Furthermore, our study population was drawn from therapy centers, encompassing individuals who had undergone cognitive-behavioral therapy (CBT) for their gambling disorder Given that CBT targets the reduction of irrational gambling-related thoughts to mitigate the influence of outcome significance on decision-making (Sylvain, Ladouceur, & Boisvert, 1997; Toneatto, 1999), it's possible that CBT contributed to a reduction in overconfidence during the present task. It could be hypothesized that untreated GD patients might exhibit more pronounced overconfidence and/or a stronger disconnection between confidence and action. Unfortunately, information about the onset of GD and gambling game preference were not assessed in this study, limiting any insight in how duration of problems and/or gambling preference could have contributed to the current findings. Finally, the current sample size of both groups was small, although similar to previous studies using this task in clinical samples (Vaghi et al., 2017). In light of the non-significant group differences observed, we must consider whether a larger sample size might reveal any distinctions between groups. Conducting post-hoc power analyses for mixed models is complex; however, it can be reasonably assumed that the potential effect sizes of confidence or action-updating differences are small, restricting the direct clinical implications of these processes in patients with GD.

In conclusion, our study investigated the connection between confidence and action in patients with GD in a volatile learning task. We found a weaker coupling between confidence and action, suggesting disrupted metacognitive control in GD, without a general positive confidence bias in GD. Additionally our findings indicated lower learning rates in GD, indicating differences in learning under volatile conditions. All in all, these findings suggest that GD is associated with disturbance in metacognitive control. Future research could advance by incorporating metacognitive ability as an important factor for comprehending disadvantageous decision-making in GD.

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Authors' contribution: MH and JL designed the study task and RJvH the study protocol. MH collected all data. MH conducted the statistical analysis. RJvH and MH wrote the first draft of the manuscript and all authors contributed to and have approved the final manuscript.

Conflict of interest: RJvH is an associate editor of the Journal of Behavioral Addictions. All other authors declare that they have no conflicts of interest.

SUPPLEMENTARY DATA

Supplementary data to this article can be found online at https://doi.org/10.1556/2006.2023.00082.

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