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Research Paper

Psychosis-proneness is associated with reduced cognitive error-monitoring during instrumental learning

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ABSTRACT

Background: People higher in psychosis-proneness tend to resist belief revision despite contradictory evidence, potentially due to impaired error-monitoring. Post-error slowing (PES), one measure of error-monitoring, is linked to working memory (WM) recruitment. With limited WM capacity, psychosis-proneness could impair belief updating through poor error-monitoring during instrumental learning.
Methods: 153 participants from Prolific were included in final analyses. To investigate how error-monitoring may explain impaired belief updating among those with psychosis-proneness, we implemented a Visuomotor Reinforcement Learning Task with varying WM loads, Interpretation Inflexibility Task, and Multidimensional Schizotypy Scale – Brief.
Results: Participants with higher positive schizotypy showed less PES at lower loads on the visuomotor instrumental learning task. WM capacity was associated positively with PES but negatively with positive schizotypy. Notably, it is only among participants higher in positive schizotypy that reduced PES associated with more severe belief inflexibility
Conclusions: These results suggest that impaired top-down error monitoring in psychosis-proneness may stem from WM limitations, leading to greater reliance on slower RL-based learning. This cognitive profile might prevent efficient belief adjustment and error correction, connecting executive function deficits in psychosis-proneness to performance monitoring and cognitive inflexibility.

1. Introduction

Individuals with or at risk for psychotic disorders tend to exhibit aberrant belief updating across various tasks (Brambilla et al., 2011; Bronstein and Cannon, 2017; Chang et al., 2016; Cicero et al., 2014; Deng et al., 2022b). This impairment often associates with delusional thoughts – persistent false beliefs that are considered a hallmark of psychosis (Bronstein and Cannon, 2017; Broome et al., 2018; Deng et al., 2022b; Feyaerts et al., 2021; Woodward et al., 2007). Why do people with or prone to psychosis fail to adjust their beliefs when encountering new information? Possible explanations include poor error monitoring and inefficient error correction, both of which likely depend on working memory (WM) capacity (McDougle, 2022; Regev and Meiran, 2014; Siegert et al., 2014). Unable to detect or sufficiently process an error, people with psychosis-proneness might not realize the need to update beliefs, even in face of disconfirming evidence. While previous research points to error processing deficits in psychotic symptoms (Corlett et al., 2007; Griffiths et al., 2014; Perez et al., 2012), it remains elusive how this impairment gives rise to aberrant belief updating. Understanding how individuals with or at risk for psychosis monitor error-related information can help to shed light on the cognitive mechanisms underlying belief inflexibility and guide potential interventions.

After an error, we tend to slow down on the next action to recalibrate our decision criteria, a phenomenon known as post-error slowing, or PES (Danielmeier and Ullsperger, 2011; McDougle, 2022; Regev and Meiran, 2014). Given previous evidence that PES effects are strongest following errors we are aware of, the magnitude of PES depends on explicit error detection (Danielmeier and Ullsperger, 2011) and working memory recruitment (McDougle, 2022). That is, PES is greater when tasks involve WM engagement, but decreases or even disappears when task demands exceed WM capacity (McDougle, 2022). In the latter case, task performance relies instead on a lower-level reinforcement learning (RL) system which slowly learns through trial and error and is resistant to short-term memory decay (Collins and Frank, 2018; McDougle and

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Collins, 2021). In a previous study, participants had decreasing PES with increasing WM demands, such that PES is absent when WM demands exceeded capacity. Under a lower load, people tend to rely on WM-based strategies, which are faster than RL-based ones, whereas when WM demands exceed capacity, people appear to switch to the slower yet decay-resistant RL system (Collins and Frank, 2012; McDougle, 2022; McDougle and Collins, 2021). Moreover, PES was better captured by a model that combines contributions of WM and RL than that of a classic RL-only model, further supporting the role of WM in generating PES (McDougle, 2022). Thus, there appears to be an interaction between the robustness of PES and the cognitive system one is deploying when encountering an error. When engaging in WM-based strategies during error processing, participants deliberately reflect on previous outcomes to properly interpret negative feedback and to better prepare for the next trial. WM recruitment thus adds deliberation time that will lengthen RTs on subsequent trials as a result of both error processing time and caution following an error. Reinforcement or more incremental learning strategies, on the other hand, are assumed to be less cognitively demanding and instead rely on gradually building up associative strength by repeatedly experiencing a stimulus-response association. Therefore, this strategy should require less time for deliberation or "thinking back" and not lead to the prospective recruitment of top-down cognitive control, thus predicting negligible PES.

People with or prone to psychosis show impaired WM (Brady et al., 2010; Forbes et al., 2009; Lee and Park, 2005; Stablein et al., 2016) but intact reinforcement learning rates (Collins et al., 2014; Collins and Frank, 2012, 2018). Given this pattern, we predicted that when WM is required for a cognitive task, such individuals would exhibit reduced or absent PES, unable to recruit WM after an error and resort to less time-consuming reinforcement-based strategies. However, previous studies have obtained mixed findings on the association between PES and psychosis. While some report attenuated or absent PES in patients with psychosis (Alain et al., 2002; Botvinick et al., 2001; Donaldson et al., 2019; Kerns et al., 2005), others found no difference (Bates et al., 2002; Becerril and Barch, 2013; Laurens et al., 2003; Mathalon et al., 2002). We believe that this inconsistency could stem in part from varied WM demands of the tasks in those studies, as PES is more reliable when WM is prominently being deployed (McDougle, 2022). To our knowledge, no prior study of PES in psychosis has controlled for WM demands of their task paradigms, so greater clarity can be achieved by examining PES at different levels of WM demand while also estimating distinct parameters of WM- and RL-related processes.

Moreover, it is also unclear based on prior work whether reduced PES in psychosis-proneness is related to positive symptoms, negative symptoms, or both. Given that aberrant belief updating is intrinsic to delusional thinking (Bronstein et al., 2019; Reed et al., 2020; Sheffield et al., 2022), if PES contributes to belief updating, reduced PES might be specifically related to positive symptoms such as delusions. At the same time, because negative symptoms (i.e., apathy, anergia, amotivation) strongly correlate with impaired cognitive control and effort (Culbreth et al., 2016; Donohoe et al., 2006; Strauss et al., 2015), lower PES might covary with this symptom dimension on cognitively challenging tasks. Differentiating these alternatives requires modeling associations of PES with positive and negative symptoms simultaneously in the same subjects. Previous studies primarily focused on error-monitoring differences between patients with psychotic disorders and healthy controls (Abrahamse et al., 2016; Kirschner and Klein, 2022; Martin et al., 2018; Storchak et al., 2021). However, cognitive disturbances are also common among those with psychotic-like experience in the general population (Barrantes-Vidal et al., 2015; Bronstein and Cannon, 2017; Lenzenweger, 2011; Staines et al., 2022; Woodward et al., 2007). Because of shared genetic risk factors between patients and people at risk, studying psychosis-proneness in the general population not only helps to establish a cognitive profile of early or sub-threshold psychosis, but also avoids treatment confounds (Barkhuizen et al., 2020; Mas-Bermejo et al., 2023; van der Meer et al., 2022). Here, we take a dimensional approach and examine how different facets of the symptoms of psychosis-proneness contribute to these differences.

The present study investigated the association between post-error slowing and psychosis-proneness using a simple instrumental learning task paradigm with varying levels of WM demand. The previously validated Reinforcement Learning Working Memory Model was applied to task performance data to parse out WM and RL capacities (Collins et al., 2014; Collins and Frank, 2012, 2018; McDougle and Collins, 2021; Yoo and Collins, 2022). Given the findings reviewed above, we hypothesized that those with higher psychosis-proneness would show attenuated PES at a lower level of WM load than those lower in psychosis-proneness. We also predicted that the reduced PES would be more strongly related to positive symptoms than negative symptoms which may help to explain the association between psychosis-proneness and belief inflexibility.

2. Methods

2.1. Participants

All participants in our study gave consent in accordance with Institutional Review Board regulations. This study was declared exempt from annual IRB review due to minimal risk to participants. The present study was not preregistered due to its exploratory nature. A total of 178 participants were recruited from Prolific. Exclusion criteria included an overall accuracy lower than 33 % (below chance) on the Learning Task, failing more than 3 attention checks on the Task or at least 1 on questionnaires, and skipping items on questionnaires (more details in procedures). Blocks with below chance accuracy were excluded, and participants were excluded for having more than 3 blocks with below chance accuracy. After applying those criteria, our final sample consisted of 153 participants (86 % of the originally recruited sample). Participant demographics are shown in Table 1.

During data collection, after collecting an initial sample with 99 participants after exclusion, we oversampled participants with higher positive schizotypy scores to compensate for the zero-inflated distribution on this measure. To oversample, we prescreened participants with questionnaires measuring different dimensions of schizotypy and paranoia. Those who scored higher than 2 out of 13 for positive schizotypy

Table 1
Participant characteristics.

	N (%) / Mean (SD)
Gender identity	
Women	102 (66.67)
Men	47 (30.72)
Non-binary	3 (1.96)
Prefer not to say	1 (0.65)
Race	
Alaskan Native	4 (2.61)
Asian	13 (8.50)
Black	27 (17.64)
Multiracial	9 (5.88)
White	93 (60.78)
Prefer not to say	7 (4.58)
Education	
Less than High School graduate	3 (1.96)
High School or equivalent	13 (8.50)
Some college, no degree	54 (35.29)
Bachelor's degree	65 (42.48)
Master's degree	15 (9.80)
M.D., Ph.D., J.D., or other advanced degrees	2 (1.31)
Prefer not to say	1 (0.65)
Ethnicity	
Hispanic	22 (14.38)
Not Hispanic	129 (84.31)
Not sure	1 (0.65)
Prefer not to say	1 (0.65)
Age	37.86 (12.53)

on the Multidimensional Schizotypy Scale – Brief (Gross et al., 2018) were invited to participate the full study, to ensure adequate variability in this trait. In total, 54 participants of our final sample were recruited through the prescreening process.

2.2. Procedure

2.2.1. Visuomotor reinforcement learning task

Participants completed an online visuomotor association learning task. This task adapted the structure from the paradigm originally used by Collins and Frank (2012). The overall goal of the task was for participants to learn a set of stimulus-response associations. On each trial participants were presented with a particular stimulus (in the form of treasure chests in different colors) for a maximum of 3 s, during which they responded with one of three key presses, "J", "K", or "L", one of which was the correct response (Fig. 1A). After responding, participants received feedback about their accuracy, which remained on the screen for 0.5 s. A fixation cross of 0.25 s preceded each stimulus presentation.

The task utilized set sizes of 2 and 4 treasure chest-outcome associations, to create different levels of WM demand. With a set size of 2, participants only needed to learn the correct responses for 2 differently colored treasure chests, while on a set size of 4, they needed to learn the correct responses for 4 differently colored chests. Participants saw each set of stimuli in a block for 15 iterations per stimulus, and the stimuli order was randomized. There were 6 blocks for each set size, for a total of 12 blocks. Within each block, there were 30 trials on a set size of 2 and 60 trials on a set size of 4. After each block, participants completed a few filler trials in which an attention check trial was embedded. The attention check presented a treasure chest not seen in the block and simply asked participants to press a particular key. Filler trials otherwise did not differ from regular trials but were not included in the final analyses of PES. Participants completed 5 filler trials for a set size of 2 and 3 filler trials for a set size 4; both set sizes involve only 1 attention check near the end of the block. Individual blocks with failed attention checks were excluded. Participants with more than 3 failed attention checks were excluded from analyses. Participants received overall accuracy feedback, including for fillers and attention checks, at the end of each block.

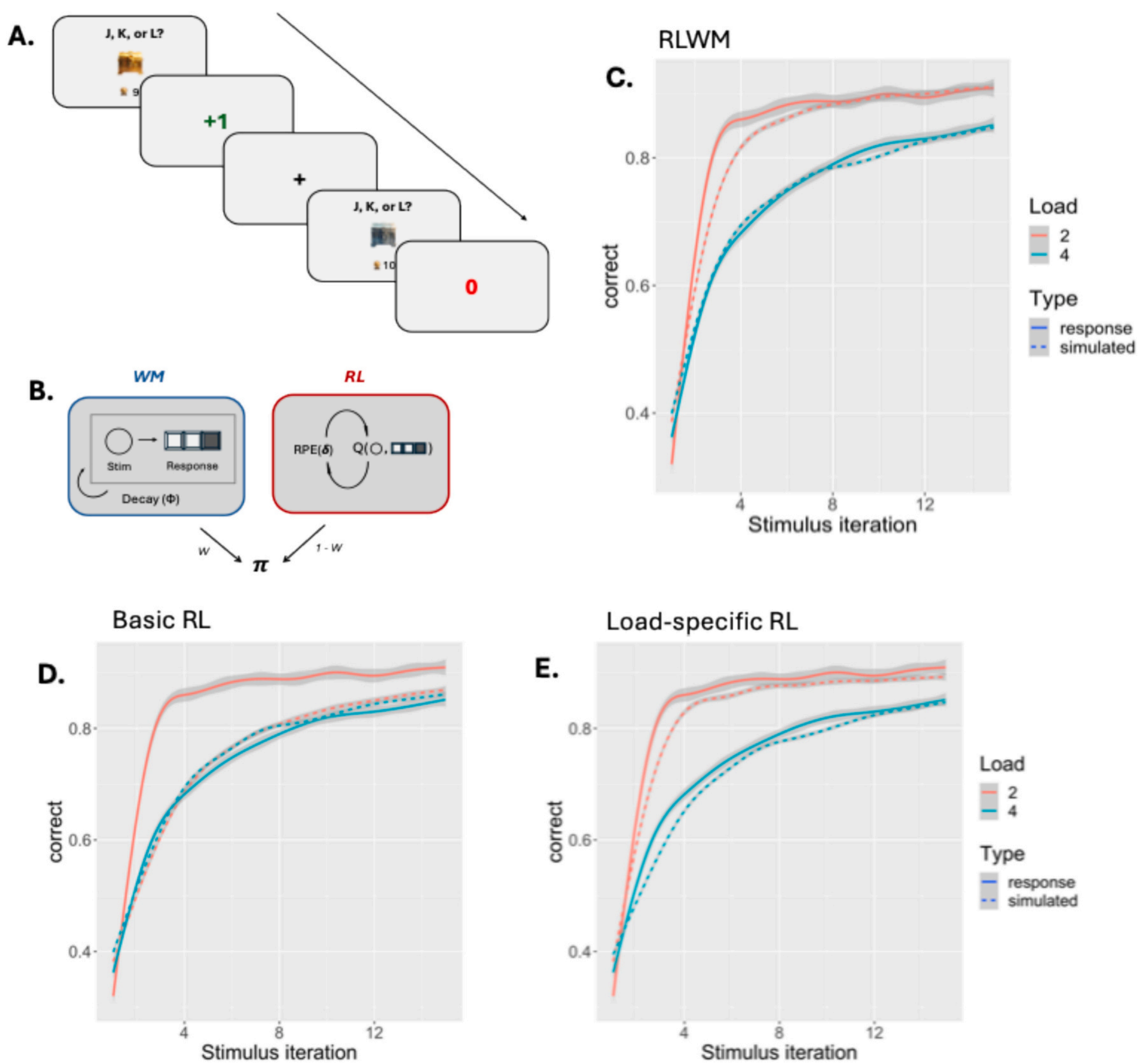

Fig. 1. Reinforcement learning task schematic, RLWM model schematic, and RLWM model fit.
(A) shows the procedure of the visuomotor reinforcement learning task, where participants use three keys to respond and receive trial-by-trial feedback (B) shows model fitting, in which the policies for WM and RL fitted separately and then combined into a final policy, adapted from McDougle (2022) (C) shows the percentages of the correct answers by participants and by model simulation. Solid lines show the accuracy of participants, and dotted lines simulated by model. The overall accuracy of the simulated choice is 76.49 %; the overall accuracy of participant response is 76.45 %, before exclusion. The prediction accuracy of the model is 68.05 % (with 33 % being the chance level accuracy). E) Simulation results of the basic RL model, with overall prediction accuracy of 67.59 %. D) Simulation results of the load-specific RL model, with overall prediction accuracy 66.44 %.

2.2.2. Interpretation Inflexibility Task (IIT)

After completing the RL task, participants completed an interpersonal BADE task developed by Deng et al. (2022a). This task consists of 24 pictorially presented interpersonal scenarios that either resolve to a positive (12 trials) or negative (12 trials) interpretation when fully disambiguated, shown in Fig. 2. Each scenario was presented in three stages: the first stage with 80 % blurring, the second stage with 20 % blurring, and the third stage with no blurring. Participants rated the plausibility of four explanations for each scenario at each stage, from "poor" to "excellent". Examples of the explanations are presented in Table 2. Two of the expanations are initially plausible lures that eventually become incompatible with the fully disambiguated picture, one true explanation which becomes increasinly plausible with disambiguation, and one absurd which does not fit at any stage of the scenario. Belief flexibility on the scenarios were defined with the interpretation flexibility index computed with the following equation (Deng et al., 2022a):

$$\textit{Interpretation flexibility index} = \sqrt{\frac{(\textit{bias score stage } 3 - \textit{bias score stage } 2)^2 + (\textit{bias score stage } 2 - \textit{bias score stage } 1)^2}{2}}$$

The bias score at each stage was computed by dividing the plausibility rating of the true explanation by the average of ratings of the lures and then multiplying this value by -1. The bias scores at the three stages were then used to compute the interpretation flexibility index.

2.2.3. Clinical measures

After completing those tasks, participants completed the Multidimensional Schizotypy Scale – Brief (MSS-B) (Gross et al., 2018), which is a 38-item scale to measure positive, negative, and disorganized schizotypy. We computed the estimated total scores on each subscale of MSS-B by adding up individual scores on each item and then divide the sum by the number of responded items. *Z*-scores of estimated sums were also computed. Participants were excluded, if they skipped three or more items on an MSS-B subscale.

Table 2
Examples of explanations on IIT.

	Positive	Negative
Lure 1	People stop you from starting a fight	People laugh at your joke
Lure 2	People are making fun of you	People think you have a great sense of humor
True	People celebrate what a great player you are	People think you can't tell a joke properly
Absurd	People discuss the smell of the field	The other people give you a comedy award

2.3. PES Measures and data analyses

All data and codes for analysis were available at https://github.com/psychack/PES-belief-flexibility. Experimental materials (task used for data collection) can be accessed at https://gitlab.pavlovia.org/wzpsych/pes_v3. For the primary analyses, we examined trial-wise patterns of error-monitoring using mixed-effects linear regressions with random intercepts and slopes for participants. For this analysis, all error trials and preceding trials were utilized regardless of the nature of the preceding response ($PES = RT_{post\text{-}error} - RT_{pre\text{-}error}$) (Dutilh et al., 2012).

There were on average 84 eligible PES trials for each participant. In addition to set size (cognitive load), positive, negative, and disorganized schizotypy, we added reward (i.e., cumulative sum of correct responses for the same stimulus up to the current trial) and delay (i.e., how many trials ago had the same stimulus appeared) to the models (Collins and Frank, 2018). Reward and delay were computed as z-scores by block, to offset the difference caused by set sizes (i.e., more delays and larger reward values in set size of four than two). Delay indirectly reflects WM processes and reward indicates progress of reinforcement learning (Collins and Frank, 2018). A correlation matrix of all variables is shown in Fig. S1. The following R code was implemented for the mixed effects model (see outputs in Table S1.):

lmer (PES ~ load + reward + delay + pos_sz + neg_sz + dis_sz + reward:

Fig. 2. Pictorial scenarios of Interpretation Inflexibility Task
Positive scenarios appear initially negative but resolves to be positive in the end, and vice versa for negative scenarios. The positive and negative scenarios here map onto explanations in Table 2.

load + reward: delay + load: delay + pos_sz: reward + neg_sz: reward + dis_sz: reward + pos_sz: load + neg_sz: load + dis_sz: load + pos_sz: delay + neg_sz: delay + dis_sz: delay + (1|participant)).

2.4. Reinforcement Learning Working Memory (RLWM) model

Collins and Frank (2012) conceptualized RL and WM as two dissociable processes deployed during this associative learning task, Fig. 1B. The RLWM model computes the learning rate, WM decay rate, WM initial weight, perseveraton, decision noise, and WM capacity from participant data. Like a classic incremental RL model (Wagner and Rescorla, 1972), learning rate is derived from the following equations:

$$Q_{t+1}(s,a) = Q_t(s,a) + \alpha\delta_t \tag{1}$$

$$\delta_t = r - Q_t(s,a) \tag{2}$$

where α is the learning rate, δ the reward prediction error, and r the reward received (either 0 or 1) on trial t. $Q(s,a)_t$ denotes the expected value on trial t of action a in response to stimulus s. Probablities for choices are transformed via the softmax fuction, where actions more likely to be selected have greater Q values. β is the inverse temperature parameter, which indicates how deterministic the expected value is in guiding the choice policy. In the present study β was fixed at 100, following the methods of Collins et al. (2014).

$$p(a|s) = \frac{e^{Q(s,a)\beta}}{\sum_i e^{Q(s,a_i)\beta}} \tag{3}$$

The WM module of the model learns the stimulus-response association with a perfect learning rate (fixed at 1), echoing the straightforward sotrage of the correct action in working memory. The WM module is prone to forgetting over time (decay rate), reflecting capacity-limited remembering:

$$W_t = W_t + \phi(W_0 - W_t) \tag{4}$$

where ϕ is the WM decay rate, which pulls W_t toward W_0, the action's initial value of 0.33 ($1/N_{actions}$). The softmax policies for WM (π_{WM}) and RL (π_{RL}) were separately computed and are then combined into the final policy:

$$\pi = p_{WM}\pi_{WM} + (1 - p_{WM})\pi_{RL} \tag{5}$$

$$p_{WM} = \rho \times \min\left(1, \frac{K}{set\ size}\right) \tag{6}$$

where p_{WM} denotes the degree of reliance or weighting on WM, ρ the initial WM weighting, and K the WM capacity. Both ρ and K thus determine the weight the agent puts on WM, p_{WM}. When set size exceeds the agent's WM capacity, the choice policy for WM (i.e., reliance on WM) decreases as a result, and learning is guidied more by the RL system.

To take into account irreducible decision noise (e.g., attention slips) in participants' learning, an undirected noise parameter ϵ is added to the final policy π:

$$\pi = (1 - \epsilon) \times \pi + \epsilon \times U \tag{7}$$

where U represents the uniform random action policy, which should be 0.33 (1/number of actions) in the present study.

Finally, participants might neglect negative feedback, thus exhibiting different learning rates depending on feedback valence (Collins and Frank, 2012, 2018). The model fits a perseveration parameter, which discounts the learning rate. Perseveration near 0 indicates minimal neglect of negative feedback, while 1 indicates total neglect:

$$\alpha = (1 - perseveration) \times \alpha \tag{8}$$

The full RLWM model was fit to participant choice data using the non-linear optimizatin package "nloptr" in R. The initial parameters values were randomized during the fitting process. The parameter values were constrained withint the following range: α = [0,1]; perseveration = [0, 1]; ϕ = [0, 1]; ρ = [0, 1]; ϵ = [0, 1]; K = [1, 5]. We optimized the model with the the R package nloptr. The starting value of each parameter was randomized with 250 iterations per participant run. Negative log likelihood was used to determine the best fit parameters within each run. Parameters with the least negative log likelihoods were averaged to represent the individuals' WM and RL contributions in learning. To validate the model, we simulated responses with the best fitting parameters for 100 iterations and averaged the results. The model showed good accuracy, replicating previous work (Collins et al., 2014), shown in Fig. 1C.

2.5. Model comparisons

Previous research found RLWM afforded better fit than basic RL models (Collins and Frank, 2012, 2018). Similar to that previous work, in this study we fit RLWM, load-based RL, and a basic RL only models to compare their fit, but primarily use parameters from RLWM for analyses given its better performance (see below).

The basic RL model includes a single learning rate and perseveration and noise parameters. The load-specific RL model includes all parameters in the basic RL model, but has separate learning rates for loads 2 and 4. We used BIC to determine the best fitting model. Consistent with previous findings, the RLWM model provided the best fit; it had the lowest BIC (689.44), compared with the load-specific (BIC = 694.74) and basic (BIC = 695.67) RL models.

To examine the association of PES with RLWM parameters and belief flexibility, we computed a summarized PES on each set size as the difference between the average reaction times (RT) on post-correct and post-error trials, $RT_{post\text{-}error} - RT_{post\text{-}correct}$.

3. Results

3.1. Effect of positive schizotypy on accuracy and PES

Positive schizotypy was associated with significantly lower accuracy, $t = -2.02$, $p = 0.04$, $\beta = -0.09$, 95 % CI [−0.18, −0.00], Fig. 3A. The positive schizotypy by load interaction was also significant, such that for a load of four, positive schizotypy was associated with significantly lower accuracy, but not for a load of two, $t = -2.82$, $p = 0.005$, $\beta = -0.25$, 95 % CI [−0.43, −0.08]. Other dimensions of schizotypy or their interactions with cognitive load were not significant in relation to accuracy, $ps > 0.30$. None of the dimensions of schizotypy affect reaction times nor were their interactions with load significant, $ps > 0.23$.

Although positive schizotypy did not have a significant main effect on PES ($p = 0.06$), its interaction with load was significant, such that higher positive schizotypy was associated with lower PES at a set size of two but not at a set size of four, $t = 2.44$, $p = 0.01$, $\beta = 0.07$, 95 % CI [0.01, 0.12], Fig. 3B. This finding suggests that in settings where WM almost fully accounts for task performance, error-monitoring appears to be reduced in positive schizotypy, perhaps reflecting reduced executive control. Positive schizotypy did not significantly interact with reward or delay, $ps > 0.28$. Other dimensions of schizotpy or their interactions with cognitive load were not significant in relation to PES, $ps > 0.30$.

3.2. Positive schizotypy and working memory capacity (RLWM parameters)

To examine the associations between schizotypy and the model-derived RLWM parameters, we ran a series of robust regressions with positive, negative, and disorganized schizotypy as predictors of each parameter. Positive schizotypy was associated with higher decay rate, $t = 1.42$, $p = 0.02$, $\beta = 0.16$, 95 % CI [0.03, 0.30], more perseveration, $t = 2.47$, $p = 0.01$, $\beta = 0.10$, 95 % CI [0.02, 0.17], and lower WM capacity, $t = -0.34$, $p = 0.003$, $\beta = -0.27$, 95 % CI [−0.45, −0.10], shown in

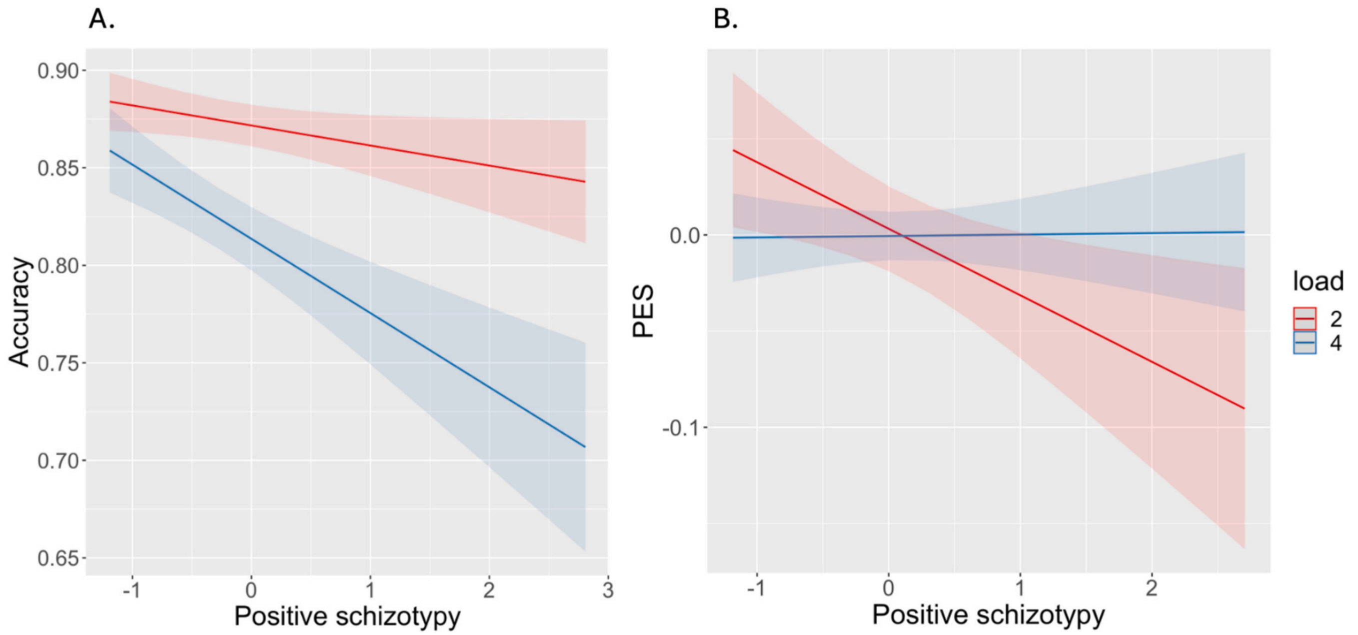

Fig. 3. Associations between PES, positive schizotypy, and accuracy
Shaded regions indicate 95 % confidence interval.

Fig. S2. Disorganized schizotypy was marginally associated with higher decision noise, $t = 1.68$, $p = 0.09$, $\beta = 0.15$, 95 % CI [−0.03, 0.32] and surprisingly, less perseveration, $t = -2.09$, $p = 0.04$, $\beta = -0.08$, 95 % CI [−0.16, 0.00]. None of the dimensions of schizotypy were related to initial WM weighting, $ps > 0.19$. Notably, learning rate was not significantly associated with any of the symptom dimensions, consistent with intact RL processes among those higher in psychosis proneness. The finding that schizotypy was related to lower WM efficacy but intact RL replicates and extends previous findings on individuals with actual schizophrenia diagnoses (Collins et al., 2014), extending this finding to subclinical populations.

3.3. PES and belief flexibility

In a robust regression with PES and the different dimensions of schizotypy as predictors and belief flexibility as the dependent variable, PES was significantly associated with higher belief flexibility, $t = 2.57$, $p = 0.01$, $\beta = 0.11$, 95 % CI [0.03, 0.20]. Positive schizotypy significantly

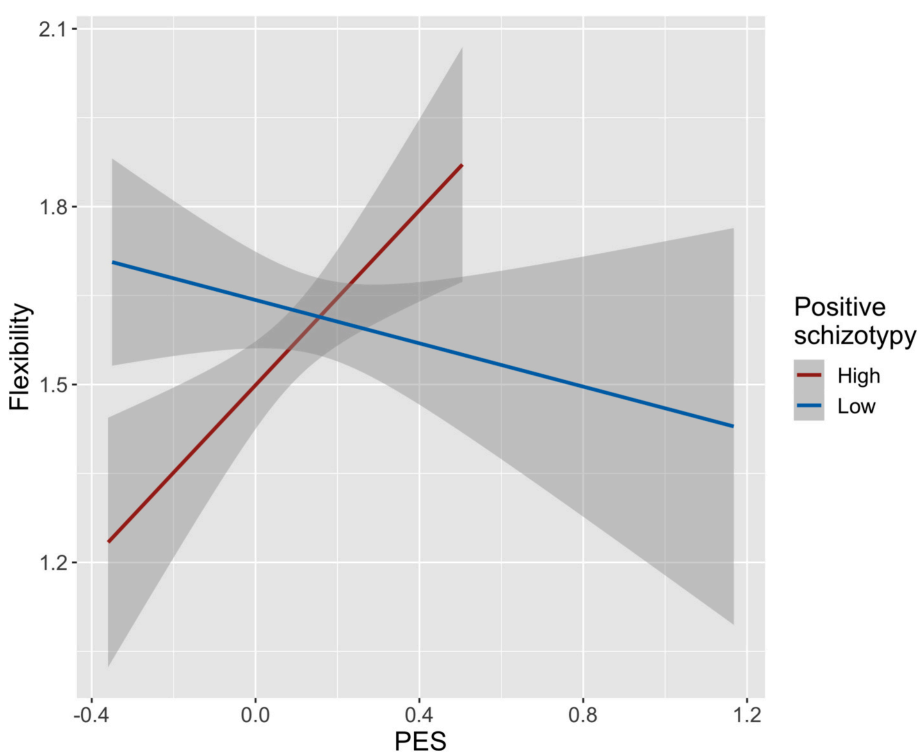

Fig. 4. PES by positive schizotypy interaction on interpretation flexibility.
Shaded regions indicate 95 % confidence interval.

interacted with PES, such that PES was more strongly associated with belief flexibility among participants higher in positive schizotypy, $t = 3.02$, $p = 0.003$, $\beta = 0.16$, 95 % CI [0.06, 0.17], Fig. 4 (see Table S2 for full regression output). The negative schizotypy by PES interaction was also significant, but with a weaker effect size, $t = 2.00$, $p = 0.05$, $\beta = 0.09$, 95 % CI [0.00, 0.17]. These results suggest that belief flexibility covaries with error-monitoring processes and may explain performance deficits related to positive schizotypy.

3.4. General patterns of PES and RL performance

We computed residuals of each model prediction of participant responses, by averaging the absolute differences between simulated and observed correct percentages. Based on a paired *t*-test $t(2669) = 3.99$, $p < 0.001$, *Cohen's d* = 0.08, 95 % CI [0.04, 0.12], the basic RL predicted participant responses more accurately on a load of 4 than 2 (Fig. 1D). The RLWM model, however, predicted participant responses more accurately on a load of 2 than 4, $t(2624) = -10.73$, $p < 0.001$, *Cohen's d* = −0.21, 95 % CI [−0.25, −0.17]. This pattern suggests more engagement of RL-based than WM-based strategies when task demands exceed WM capacity.

We also examined overall patterns in the data (i.e., without respect to individual differences in psychosis proneness) to facilitate comparison with prior studies. Participants were generally less accurate with higher cognitive load (i.e., on a set size of four vs two), $t = -6.88$, $p < 0.001$, $\beta = -0.52$, 95 % CI [−0.67, −0.37]. Higher load was associated with significantly lower PES, $t = -4.88$, $p < 0.001$, $\beta = -7.65\text{e-}05$, 95 % CI [−0.04, 0.04], and longer RT, $t = 12.22$, $p < 0.001$, $\beta = 0.96$, 95 % CI [0.80, 1.11], replicating previous work (McDougle, 2022). Higher reward (i.e., cumulative correct trials) was associated with significantly higher PES, $t = 8.19$, $p < 0.001$, $\beta = 0.05$, 95 % CI [0.03, 0.07]. The main effect of delay was not significant. The load by reward interaction was significant, such that higher reward was associated with greater PES on a set size of two but not on a set size of four, $t = -6.81$, $p < 0.001$, $\beta = -0.05$, 95 % CI [−0.07, −0.04]. Reward and delay significantly interacted, such that with higher delays, the association between PES and reward was less strong than with lower delays, $t = -3.47$, $p < 0.001$, $\beta = -0.03$, 95 % CI [−0.05, −0.01].

Spearman correlations were used to examine the association between each RLWM parameter and PES. Perseveration and decay rate of WM was significantly associated with lower PES, $rs(300) > -0.33$, $ps < 0.001$. WM capacity, initial WM weighting, and learning rate associate with higher PES, $rs(300) > 0.14$, $ps < 0.02$, shown in Fig. S3. Similarly, those parameters also significantly correlate with accuracy, $rs(300) > 0.12$, $ps < 0.04$.

4. Discussion

In the present study we examined attenuated PES in psychosis-proneness and its potential as an explanation for belief inflexibility. Results of the study confirmed impaired error-monitoring in psychosis-proneness through attenuated PES, reflecting reduced cognitive effort in error-monitoring and correction. Notably, participants with higher positive schizotypy showed less PES than those lower in this trait, but only under lower WM loads when the task primarily involved WM recruitment. This pattern, along with RLWM modeling results, suggests that impaired WM capacity at least partially contributes to error-monitoring deficits in psychosis-proneness. Further, attenuated PES was only observed in relation to positive schizotypy (as opposed to negative or disorganized schizotypy), indicating differential relevance of error processing deficits to symptoms reflecting impaired reality testing. The PES by positive schizotypy interaction in relation to belief flexibility also suggests that error processing deficits may help to explain belief updating impairments among those prone to psychosis.

4.1. WM impairment as mechanism for error-monitoring deficits in psychotic symptoms

The load-specific PES reduction in positive schizotypy supports WM impairment as a mechanism contributing to error-monitoring deficits in psychotic symptoms. Those higher in positive schizotypy may have relied more on RL-based strategies on both loads of 2 and 4, while participants lower in this trait likely did so only (or primarily) on a load of 4. Due to limited WM capacity, those with higher positive schizotypy probably relied more on RL-based learning even under lower WM demand, leading to reduced PES (McDougle, 2022). Supporting this interpretation, and in line with prior work using RLWM model (Collins et al., 2014), positive schizotypy was associated with a higher decay rate and lower capacity of WM but an intact reinforcement learning rate. Unable to exert WM after an error even with lower load, those with higher positive schizotypy had to rely on RL throughout the task. Given these results, inconsistencies in previous studies of PES differences in psychosis (Abrahamse et al., 2016; Alain et al., 2002; Becerril and Barch, 2013) are likely explained by the between-study differences in WM demands of the tasks employed. It is only when the task requires WM and has a load within the capacity of the general population that participants with psychotic symptoms may show attenuated PES. This explanation was not possible to test in previous work, because WM load was not directly manipulated.

We did not find effects of negative schizotypy on accuracy or PES, despite its established relationship with working memory impairment (Donohoe et al., 2006). Multicollinearity between dimensions of schizotypy is an unlikely explanation, given its low pairwise correlation with positive and disorganized schizotypy. Negative schizotypy primarily relates to amotivation and impaired processing speed (Barch et al., 2014; Chang et al., 2020; Fervaha et al., 2014), while positive schizotypy (such as paranoia) affects prediction error processing and cognitive biases (Corlett et al., 2019; Corlett et al., 2007; Reed et al., 2020; Sheffield et al., 2022). PES, in the context of our experimental design, could be initiated by prediction error processing and further driven by WM recruitment, both of which are impaired in positive schizotypy. The lack of effect of negative schizotypy suggests the results are not explained by differences in motivation or processing speed.

4.2. PES associates with belief flexibility among those with psychosis-proneness

The PES by positive schizotypy interaction on the IIT performance measure also suggests impaired error-processing as a plausible contributor to belief inflexibility in psychosis-proneness. Typically, people with psychosis-proneness fail to adjust their beliefs in the presence of disconfirming evidence (Deng et al., 2022b; Eisenacher and Zink, 2017). We found here that those higher in positive schizotypy showed attenuated PES at a low WM load, suggesting difficulty in post-error WM recruitment even under lower cognitive demand. As both error detection and WM recruitment are necessary to process observations discrepant with prior beliefs, reduced PES should associate with less belief updating in those with higher positive schizotypy. If this result can be generalized beyond the present task, people with positive schizotypy may not deploy WM-based processes to make sense of errors in real-time. Instead, such individuals might rely heavily on reinforcement-based strategies, which are slow to adapt. Without having made sense of or discerned these discrepancies, people with psychosis-proneness might not recognize the need to adjust beliefs, potentially leading to their tendency to preserve erroneous beliefs. For example, having once misinterpreted others' actions as ill will, those with positive schizotypy might not be able to self-correct out of a false and enduring sense of suspicion, because they do not actively detect or process information discrepant with this schema.

4.3. Limitations

There are several limitations of this study. One of the aims was to clarify inconsistencies in the current literature, which primarily compared PES between patients with schizophrenia and healthy controls. However, our sample was drawn from the general population and measured psychosis-proneness with self-reported schizotypy, which might not reflect all aspects of schizophrenia or symptoms experienced by patients. By oversampling positive schizotypy, we compensated for the variability in symptom severity in the general population. Further, psychotic experience exists on a continuum, and such symptoms are present among the non-patient population (Hinterbuchinger et al., 2023; Staines et al., 2022). Nevertheless, because our findings are based on subjects with subclinical psychotic experiences, future studies of patients with psychotic disorder diagnoses are needed to fully establish cognitive load and WM capacity as moderators of the association between PES and psychosis-proneness. Although our study integrated a computational model to parse the contributions of WM and RL to PES, drift diffusion modeling could help us refine the contributions of evidence accumulation and decision thresholds in PES (Dutilh et al., 2012). However, this model was not applied in the present study because it requires a binary stimulus-response task structure that is at odds with our data structure.

5. Conclusion

In the present study, those higher in psychosis-proneness showed reduced error-monitoring in the form of attenuated PES, an effect that was moderated by the WM demands of the task and was related to less belief revisioning on a Bias Against Disconfirmatory Evidence task. With less WM capacity, individuals higher in psychosis-proneness likely relied on intact RL-based learning which is slower than WM-based learning to adapt to errors (McDougle and Collins, 2021). These results suggest that impaired belief revision in psychosis-proneness is explained by reduced efficiency in leveraging negative prediction errors and exerting cognitive control to adapt response strategies in the face of errors.

CRediT authorship contribution statement

Wanchen Zhao: Writing – review & editing, Writing – original draft, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Samuel D. McDougle:** Writing – review & editing, Supervision, Methodology, Formal analysis. **Tyrone D. Cannon:** Writing – review & editing, Supervision, Methodology, Formal analysis.

Declaration of competing interest

Authors declare no competing interest that could inappropriate influence or bias this research.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.scog.2025.100408.

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