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Delusional self-confidence? Trait perseverance is associated with increased brain activity reflecting confidence about own performance in a dot random motion task

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ABSTRACT

Most people perform best when being moderately challenged, while their motivation drops for very easy or very difficult tasks. We investigated the impact of task difficulty on task engagement, mood state, and the P3 component of the event-related brain potential (ERPs) reflecting the formation of confidence about performance. A group of young adults completed a random dot motion task with easy, moderate, and difficult blocks. We analyzed possible moderation effects of personality traits and self-regulation, as they explain tendencies to keep consistent motivation and persevere despite difficulties. Results showed, contrary to hypotheses, a benefit in mood and engagement when the task was easy rather than moderate or difficult. Interestingly, low perseverance predicted confidence about own performance when the task was easy, as evidenced in larger P3 amplitude. In contrast, participants scoring high in perseverance showed greater confidence in their responses in the difficult condition. Results did not support an explanation in terms of affect regulation. We propose that uncertainty about one's own ability could activate top-down confidence in persevering individuals, and the belief that if they work hard, will eventually succeed. This top-down confidence in the brain may be the source of the sustained effort characteristic of perseverance.

1. Introduction

Motivation explains the mechanisms for the initiation and withdrawal of behavior and why some people persevere despite fatigue or uncertainty about the outcome of their effort (Geen, 1995). Individual differences in motivational and emotional tendencies most likely explain why some people persevere and succeed, whereas others drop out. The present study investigates the neurocognitive mechanisms of the interplay between task difficulty, engagement, and mood, and the role of differences in personality and self-regulation traits.

The relationship between difficulty and motivation typically follows an inverted U-shape distribution. That is, very easy or very difficult tasks have a negative impact on our motivation, but engagement increases when we feel that the task demands match or slightly challenge our capacities (Csikszentmihalyi, 2014). Motivational intensity theory argues that effort mobilization follows the conservation principle, investing resources in a very difficult task is pointless if we cannot reach success because resources will be wasted (e.g., Richter et al., 2016). Task difficulty serves as an indicator of the resources required for successful task completion and is therefore a core aspect of motivation. For instance, hand grip force increases linearly with task difficulty until the point where the task becomes impossible (Richter et al., 2016). Hence, having a chance to success is important, and finding tasks that are challenging yet achievable is important for maintaining motivation (Guadagnoli & Lee, 2004). This issue might be particularly important in an educational context, e.g. in the case of planning engaging activities for young adults.

Emotions are the basis of motivational tendencies influencing perceptual decisions and response execution (Pessoa, 2009). Success in a task maximizes positive affect through positive emotions like pride,

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whereas errors can elicit negative affect. In those situations, behavior can serve to regulate the hedonic consequences of performance. For example, individuals might persevere to maintain the positive mood associated with success, or contrarily, to repair the negative mood associated with failure. Similarly, individuals may disengage from the task as a coping mechanism to deal with the negative mood associated with very high difficulty. Thus, a particular mood might have different or even opposite motivational implications, mobilizing effort to repair negative emotion or giving up effort to cope with failure (Gendolla, 2000). Personality traits describe stable motivational and emotional tendencies which may explain different instrumental effects of mood on behavior coping with difficult tasks. For example, individuals with high self-efficiency beliefs expect a good performance, must feel negative emotion when failing, and increase their effort to accomplish the task, while those with low behavioral standards would give up (Cervone et al., 1994).

In the big-five model of personality, trait *emotional stability* describes differences in the tendencies to experience negative emotion and susceptibility to stress (Costa Jr. & McCrae, 2008), which have a negative impact on the motivation to pursue difficult goals. Trait *conscientiousness* describes individual differences in the motivation for achievement, self-discipline, and sense of duty, which should predict consistency in motivation despite facing difficulties.

Self-regulation strategies describe individual tendencies and abilities to regulate behavior and cognition to achieve future outcomes. For example, *perseverance* describes the tendency to pursue goals or complete tasks despite encountering difficulties, and *learning from mistakes*, describes the capacity to reflect on mistakes, understand what went wrong, and adjust future behavior. These strategies should impact the way individuals handle difficult tasks.

1.1. Effects of task difficulty on ERPs: confidence about own performance

Confidence about our own performance in visual tasks gradually increases based on cumulative evidence from visual information, up to a certain point when we can decide and then execute a behavioral response. When the task is easy, confidence about the correct responses can be reached quickly, speeding up reaction times (RTs.) As difficulty increases, certainty about the correct answer diminishes and RTs slow down. In the random dot motion (RDM) task participants see a cloud of moving dots and are asked to determine the main movement direction of the dots (e.g., left or right). Dots are divided into two types: signal dots, which move coherently in a specific direction, and noise dots, which move randomly in various directions. This task can be used to study how confidence in the decision builds up as a function of dot coherence.

The timeline of neurocognitive processes involved in the built up of confidence in RDM tasks can be investigated using electroencephalography (EEG). Several features of the EEG signal have been related to confidence formation, for instance, the maximum amplitude and latency values of a long-lasting P3 event related potential (ERP) peaking 300–600 ms after stimulus onset (Shooshtari et al., 2019). Another study also reported a similar P3 modulation (350–500 ms) increasing gradually in amplitude with confidence about one's own performance, providing a robust index of subjective confidence without requiring participants to make explicit judgments (Boldt & Yeung, 2015). A somewhat earlier (250 to 350 ms after stimulus onset) centroparietal positive potential (CPP), whose amplitude increased up to the moment of response execution was associated with the accumulation of perceptual evidence (Kelly & O'Connell, 2013).

The present study examined the neurocognitive mechanisms involved in the association between task difficulty, engagement, and mood. We investigated ERP correlates of confidence formation in a RDM task in which trials ranged from easy to very difficult (unsolvable). Previous EEG studies on this topic did not consider how individual differences in stable traits moderate confidence formation in the brain. This seems an important point to consider, however, as individuals differ considerably in the way they react to and cope with challenging tasks.

The hypotheses of this study were pre-registered before the data collection started (Recio et al., 2023). Replicating previous findings, we expected participants' performance in the task to reflect the manipulation in difficulty, that is, accuracy should be close to ceiling in the easy condition and gradually decrease with increasing difficulty, up to reaching chance level in the difficult condition (H1a). Likewise, RTs should be faster in the easy condition and increase for moderate and difficult trials (H1b). We predicted task engagement and self-reported ratings of positive emotions to be maximal for moderate difficulty, in which the RDM task is challenging but still achievable, compared with easy or difficult trials (H2). In the EEG data, we expected a smaller P3 component (350–600 ms) with increasing task difficulty, because participants will be less confident about their responses (H3).

As novelty, we also expected individuals scoring high in conscientiousness and high in perseverance to show greater engagement in the difficult condition than those with lower scores, resulting in a linear rather than quadratic trend (H4). Finally, trait emotional stability and learning from mistakes should report less negative emotion and less engagement when the task is difficult, as a coping mechanism to avoid wasting resources in an unsolvable task (H5).

2. Method

2.1. Participants

Seventy participants were recruited using posters posted on University Campuses and social media. They needed to be between 18 and 30 years old, not receive psychopharmacological treatment, have at least B1 proficiency level in Spanish, and normal or corrected-to-normal vision. All gave written informed consent prior to participation and received 15€ at the end of the study. The study was approved by the local committee (Institutional Review Board, 00003099). One participant had a failure to record the EEG, one had excessively noisy EEG data, and two further were excluded whose accuracy in the easy condition was 2.5 SDs below the group mean. The final sample consisted of 66 participants (43 women, 4 left-handed), mean age = 24 years old (SD = 3.8). Most participants were students ($n = 46$), two were unemployed, and 18 were employed. They had diverse educational levels: elementary school (1 %), high school or vocational training (40 %), college (59 %).

2.2. Materials and procedure

All participants signed written consent and could ask questions about the study or data handling prior to participation. First, they completed a demographic questionnaire, the Spanish version of the Big-Five Inventory XS (Gallardo-Pujol et al., 2022), and the Spanish Short Self-Regulation Questionnaire (Garzon Umerenkova et al., 2017), using a Qualtrics survey on a laptop computer. They were then prepared for the EEG recording before completing the RDM task, which was run using PsychoPy (Peirce et al., 2019) and consisted in determining the main direction of movement of a cloud of 100 dots (dot speed = 3.5, dot lifetime = 5). Task difficulty was manipulated by changing the coherence of dot left/right dot movement, which was 80–100 % in the easy condition, 20–40 % in the moderate condition, and to 0–10 % in the difficult condition. See Fig. 1 for trial description.

The complete RDM task included 180 trials, split into blocks of 60 trials for each of the difficulty levels. Block order was counterbalanced using a Latin square design based on six runs, see preregistration for details. Every 15 trials (i.e., four times per block) participants rated their mood state, task engagement, and perceived difficulty in that block using a computer mouse and a visual analog scale with 11 visible ticks. The questions and scales remained on the screen until participants made a choice: *"What is your mood state during this block?", "Rather negative/ Neutral/Rather positive"*; "*How much are you enjoying this block?", "Little/ Normal/Quite a lot*"; and *"How difficult do you find this block?" "Rather*

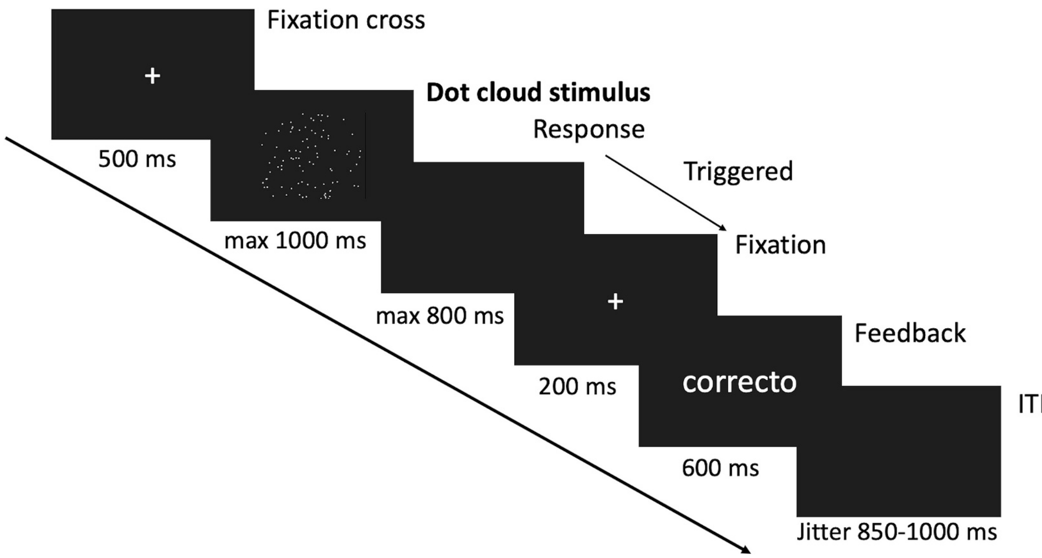

Fig. 1. Example of a trial with feedback about a correct answer.
Note. Each trial started with a fixation cross presented for 0.5 s, then the dot cloud stimulus appeared on the center of the screen for 1 s (or less if a response occurred). Participants indicated the movement direction of most of the dots in the cloud by pressing either the left or right arrow keys on a computer keyboard. Response time was limited to 1.8 s from stimulus onset. Once the response was collected, the stimulus disappeared and a fixation cross appeared for 0.2 s, followed by the words correct/incorrect (font color white, size 40, 0.6-s duration), which provided feedback about participant's performance on each trial. Following a blank screen (jittered duration 0.85 to 1 s), the next trial started.

easy/Normal/Rather difficult".

2.3. EEG processing

Details about EEG recordings are provided in the supplementary material. EEG data was analyzed using the MNE Python library (Larson et al., 2024). It was filtered with a low-pass filter (30 Hz, 24 dB/oct) and transformed to average reference including both mastoids. Blinks were removed by means of independent component analyses. The corrected signal was epoched from 0.2 s before to 1 s after stimulus onset, and baseline corrected using the average of the first 0.2 s. Epochs with amplitudes exceeding +200 or − 200 μV, voltage steps >100 μV between adjacent sampling points, and amplitude differences >300 μV within a given segment in any channel were considered artefacts and removed.

3. Results

We fitted separate LMMs, using the lmer library (Bates et al., 2015) in R to estimate the effect of task difficulty on accuracy, RTs, rating scales, and ERP amplitudes. By-participant random intercepts and random slopes were included in the random effects. Effects of each of the big-five and self-regulation traits, and their interactions with difficulty, were also assessed. We used difference contrasts using the moderate condition as baseline, and comparing it to easy and difficult trials (Schad et al., 2020), as these comparisons were essential for our behavioral hypotheses. Results for all models are provided in supplementary material.

3.1. RTs and accuracy data

Table 1 shows percentage accuracy and RTs in milliseconds (ms) for different conditions. Fig. 2 shows violin plots for performance and ratings data.

As expected in H1a, accuracy was higher in easy than moderate trials ($\beta = -16.99$, $SE = 1.77$, $t = -9.59$, $p < .001$), and lower in difficult than moderate trials ($\beta = -13.79$, $SE = 1.82$, $t = -7.59$, $p < .001$). Models testing H5 did not reveal any significant main effects or interactions of personality or self-regulation traits (all $ps > 0.05$). As expected in H1b,

Table 1
Means and standard deviations for RTs, accuracy, and ratings on mood, engagement and perceived difficulty.

	Easy	Moderate	Difficult
	M (SD)	*M (SD)*	*M (SD)*
Reaction times (ms)	459.94 (82.3)	487.00 (118.1)	486.02 (113.6)
Accuracy (%)	81.64 (13.7)	64.65 (14.9)	50.86 (6.3)
Mood	7.0 (1.9)	6.2 (2.1)	5.6 (2.0)
Task engagement	6.9 (2.0)	6.0 (2.2)	5.5 (2.2)
Perceived difficulty	4.0 (2.5)	5.9 (2.1)	7.1 (1.6)

RTs were faster in the easy compared to the moderate condition ($\beta = 27.17$, $SE = 9.85$, $t = 2.76$, $p < .01$), however did not differ significantly between moderate and difficult conditions ($p > .05$). Personality and self-regulation traits (H5) did not result in main or interaction effects, except for a main effect of learning for errors ($\beta = -34.36$, $SE = 16.07$, $t = -2.14$, $p = .04$), indicating that RTs were faster for individuals scoring high in this trait, across all difficulty conditions.

3.2. Participants' ratings on mood state, task engagement, and perceived difficulty

Ratings of engagement were highly correlated with mood $r(196) = 0.87$, $p < .001$. Perceived difficulty was negatively correlated with mood and engagement $r(196) = -0.35$ and -0.40, respectively, $ps < 0.001$, same as performance accuracy, $r(196) = -0.32$ (mood), -0.36 (engagement), $ps < 0.001$. Contrary to H2, positive mood was lower in trials with moderate than easy difficulty ($\beta = -0.84$, $SE = 0.21$, $t = -4.09$, $p < .001$), and decreased further in trials of high difficulty ($\beta = -0.53$, $SE = 0.17$, $t = -3.12$, $p < .01$). Similarly, task engagement increased in easy trials ($\beta = -0.93$, $SE = 0.20$, $t = -4.63$, $p < .001$) relative to moderate difficulty, and decreased in difficult trials ($\beta = -0.47$, $SE = 0.19$, $t = -2.53$, $p < .05$). Also, relative to moderate conditions, perceived difficulty decreased in easy trials ($\beta = 1.92$, $SE = 0.26$, $t = 7.33$, $p < .001$), but increased in difficult trials ($\beta = 1.23$, $SE = 0.23$, $t = 5.34$, $p < .001$).

The LMM estimating fixed effects of big-five traits, revealed main

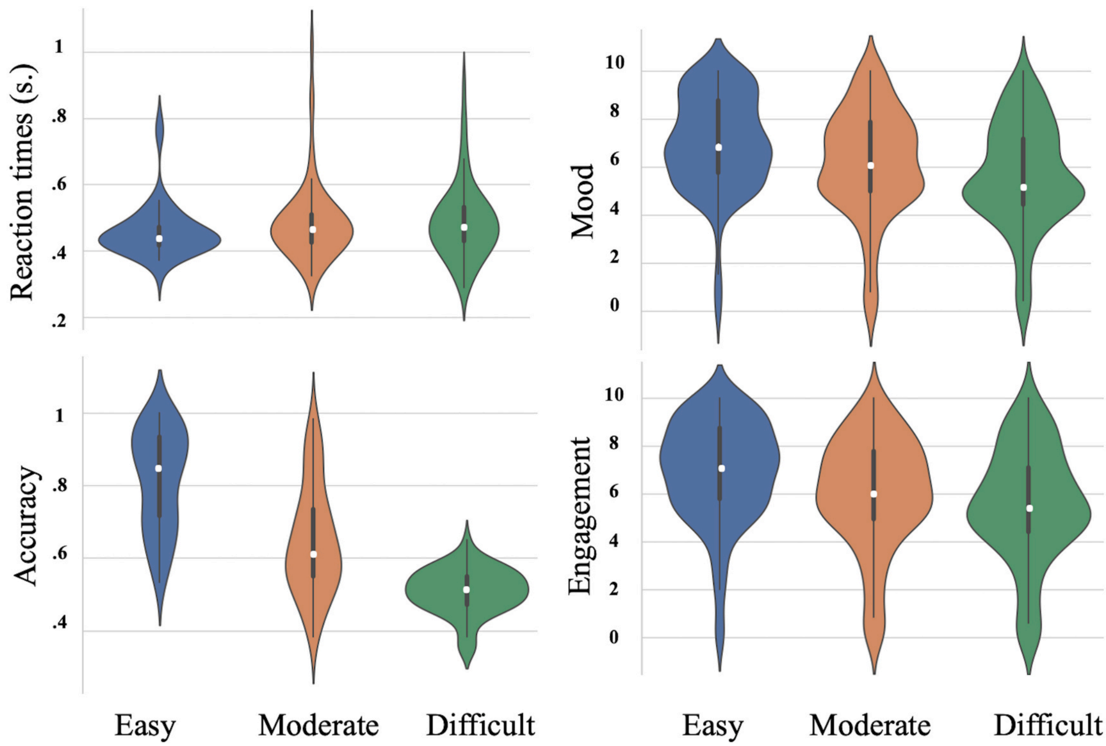

Fig. 2. Violin plots show the dispersion of values of performance and ratings data. White dots indicate medians, thick whiskers are quartiles, and thin whiskers upper and lower data.

effects of openness on ratings of mood and engagement, indicating that more positive mood ($\beta = 0.27$, $SE = 0.08$, $t = 3.38$, $p < .01$), and greater engagement ($\beta = 0.22$, $SE = 0.09$, $t = 1.45$, $p < .05$) were associated with high openness.

3.3. EEG data

Differences in mean ERP amplitudes between conditions were estimated as fixed effects in LMMs using the Statsmodels library in Python (Seabold & Perktold, 2010), using the easy condition as reference, as we expected a linear decrease in amplitude from easy to difficult. We fitted further LMMs estimating fixed effects and interactions of difficulty with big-five and self-regulation traits. By-participant random intercepts and random slopes were included, to test that the effect of difficulty on CPP amplitude could differ between participants depending on their personality traits. Other ERP studies reported effects of task difficulty between 250 and 600 ms in region of interest (ROIs) including two to three channels centered around CPz (Boldt & Yeung, 2015; Kelly & O'Connell, 2013; Shooshtari et al., 2019). Consistent with previous studies, differences in amplitude between conditions started at 250 ms post-stimulus onset and were sustained up to 600 ms, as a long-lasting centroparietal positivity peaking around 400 ms (see Fig. 3). We focused the analysis on the 100-ms time window around the peak, i.e., 350–450 ms at three sites (Cz, CP1, CP2) because maximal amplitude is considered to represent confidence in perceptual decisions (Shooshtari et al., 2019).

Amplitudes in the ROI between 350 and 450 ms after stimulus onset were highest for easy trials and decreased significantly in moderate ($\beta = -1.91$, SE = 0.24, z = −7.96, $p < .001$), and difficult conditions ($\beta = -2.69$, SE = 0.24, z = −2.69, $p < .001$). When adding questionnaire scores, we found that high conscientiousness ($\beta = -0.24$, $SE = 0.13$, $z = -1.88$, $p = .06$) and high perseverance ($\beta = -0.58$, $SE = 0.37$, $z = -1.56$, $p = .12$) resulted in a marginally significant reduction of P3 amplitude across all conditions. Most interestingly, a significant interaction between perseverance and task difficulty emerged (Fig. 4; $\beta = 0.78$, $SE = 0.32$, $z = 2.62$, $p = .013$). While a smaller P3 was found for low vs. high perseverance in the easy condition, this pattern was reversed in the difficult condition, where individuals scoring high in perseverance had larger P3 amplitudes. None of the other personality and self-regulation traits yielded a significant effect (all $ps > 0.1$).

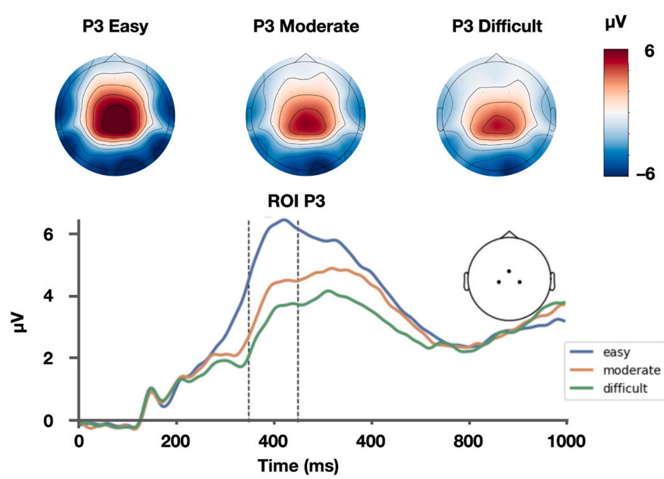

Fig. 3. Main effect of task difficulty on the P3 amplitudes in a group of 3 centro-parietal sites and scalp topographies in the time window 350–450 ms.

3.4. Inverse efficiency analysis

To further explore the relationship between performance and P3 amplitude, inverse efficiency scores (IES), a measure of performance that controls for speed-accuracy tradeoff (Liesefeld & Janczyk, 2019), were computed by dividing RT by percentage of accuracy. We then fitted a linear regression model to predict IES from the P3 mean amplitude (see Fig. 5). The overall model was statistically significant ($F(1,196) = 36.38$, $p < .001$), explaining approximately 15.7 % of the variance in

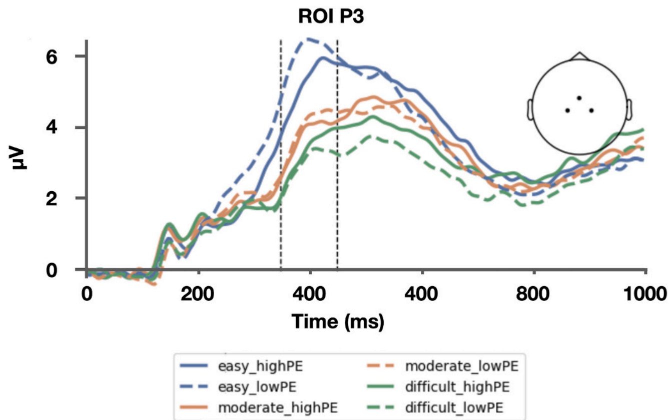

Fig. 4. Moderation of the main effect of task difficulty on the P3 amplitude by perseverance (PE). Solid lines show the effect for individuals scoring high in PE and dashed lines for those scoring low.

performance ($R^2 = 0.157$). The regression coefficient for the P3 amplitude was statistically significant ($\beta = -43.83$, $t(196) = -6.03$, $p < .001$, 95 % CI [−58.16, −29.50]), indicating that increased brain activity (a possible proxy of confidence) was associated with improved efficiency (i.e., lower IES). We also regressed ratings of perceived difficulty on the P3 (Fig. 5 right). The regression model was significant ($F(1,196) = 14.57$, $p < .001$), explaining 6.9 % of the variance in perceived difficulty ($R2 = 0.07$), and confirmed that the P3 amplitudes also predicted difficulty at the subjective level ($\beta = -0.26$, $t(196) = -3.94$, $p < .001$, 95 % CI [−0.39, −0.12]).

4. Discussion

We investigated the impact of task difficulty on mood, engagement and confidence formation in the brain in a group of young adults. Main interest was on the role of individual differences in self-regulation and big-five personality traits on confidence formation. We expected task engagement and positive mood to be maximal when the task was challenging but still achievable. We also tested the hypothesis that conscientious and perseverant individuals would show greater engagement when the task is difficult. All behavioral measures (RTs, accuracy, and ratings) revealed significant linear trends associated with task difficulty. Contrary to our expectations, positive mood and task engagement were maximal in the easy condition and decreased hand in hand with performance accuracy, as dot coherence diminished, and the task became more difficult. Mirroring the behavioral effect, the amplitude of the P3 component decreased with increasing task difficulty. Interestingly, however, the P3 effect interacted with individual differences in perseverance.

Data from performance accuracy largely confirmed the intended manipulation (H1) and previous studies. Hit rates were on average ca. 80 % in the easy condition and decreased to 65 % in the moderate and to chance level (51 %) in the difficult condition, confirming that the latter was impossible to solve because dots moved in random directions. Participants' ratings of perceived difficulty linearly increased by reducing signal dots coherence, confirming that our manipulation worked at the subjective level. Similarly, RTs were slower in the moderate and difficult trials, relative to the easy ones.

As suggested by (Csikszentmihalyi, 2014) we expected positive mood and task engagement to be maximal in the condition of moderate difficulty (H2), in line with the idea that engagement is largest when we feel that task demands match or slightly challenge our capacities. Contrary to our hypothesis, results showed the greatest engagement and most positive mood in the easy condition, which diminished with increasing difficulty. This was an unexpected finding and can be explained by considering performance results. Accuracy data yields the question of whether the task was more difficult than we planned, at least for some individuals. We expected ceiling effects in the easy condition, but this was not exactly the case. As can be seen in Fig. 2, although most participants had close to ceiling performance in the easy condition, and few of them also in the moderate one, others seemed to struggle to identify the correct answer, with a few participants performing close to chance level even in easy trials. Especially the moderate condition turned out to be more difficult than expected for some participants. The difficulty of the RDM parameters in each condition had been calibrated based on a pilot study carried out with a non-overlapping sample of 20 participants, and we assumed that this calibration could be taken as nominal difficulty. However, results indicate that individual differences in the ability to solve the RDM task probably played a role, which we did not control for. Possible implications of this issue will be discussed below.

In the ERPs, we observed a long-lasting P3 peaking around 400 ms after the onset of the dot cloud stimulus, which was largest for the easy condition and progressively decreased in the moderate and difficult conditions. This suggests that participants were more confident making decisions regarding dot movement when coherence was high (easy condition), and confidence diminished making the decision more difficult by reducing signal dot coherence (moderate and difficult

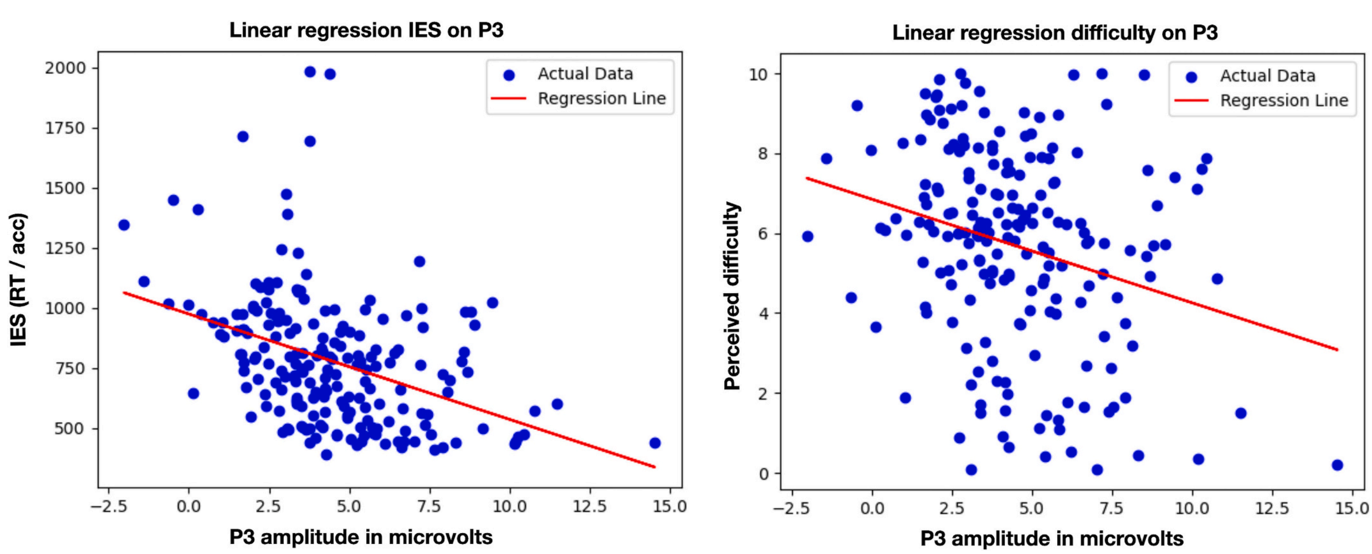

Fig. 5. Regression of the IES (left), and perceived difficulty (right) on the P3 amplitude (in microvolts).

conditions). This confirmed our hypothesis (H3) and replicates findings of previous ERP studies using the RDM task (Shooshtari et al., 2019). The P3 amplitude significantly predicted IES scores and ratings of perceived difficulty, indicating that it also reflects confidence at the subjective level (Boldt & Yeung, 2015).

We observed an interesting, unexpected finding in the ERP data, that is, the amplitude of the P3 component in the time window 350–450 ms showed a trend for larger amplitudes for individuals scoring high vs low in traits conscientiousness and perseverance. Most interestingly, the P3 amplitude showed a significant interaction of difficulty by perseverance, namely, the pattern of results in the difficult condition, with larger P3 amplitudes for participants with high compared to low perseverance, was opposite in the easy condition, with larger P3 amplitude for low vs high. To the best of our knowledge, such an effect has not been reported before and gives us a hint of why perseverant individuals maintain effort in difficult tasks. Our finding points to the possibility that young adults who persevere seem to be less confident about perceptual decisions than those scoring low when the task is easy, but then they show more confidence when the task becomes difficult, which fuels their effort. The most striking aspect of this finding is that the difficult condition in our RDM task was not solvable using bottom-up visual information, suggesting that this confidence could be to some extent delusional, and top-down controlled. The question then is, what drives this top-down confidence?

One possible explanation is that the struggle of not performing well generates negative emotion, and then persevering people use effort and behavior as instruments to regulate negative emotion. However, conscientiousness and perseverance had no impact on mood state and engagement (H4) in our data, which does not support the hypothesis around affect regulation. Instead, our data suggests that it is the formation of confidence in their perceptual decision in the brain what pushes them to persevere, even when the task is impossible to solve. The significant interaction between perseverance and task difficulty suggests that this mechanism is activated when the task is very difficult. In conditions where the decision is easier, high perseverance is instead associated with lower confidence.

This finding can be attributed to the activation of different mindsets. Individuals with a *fixed mindset* believe success comes from their own ability, whereas those with a *growth mindset* view success as a result of effort and perseverance (Dweck, 2006). Deimen and Wirtz (2022) indicate that confidence about one's own ability determines this control belief characteristic of the growth mindset. For instance, students might give up if they think a task is beyond their ability, or persevere in their effort if they think success can be achieved through hard work (Deimen & Wirtz, 2022). Hence, when persevering individuals face uncertainty about their performance in an unsolvable task like the RDM task used here, it appears to activate a growth mindset. This, in turn, reinforces the belief that effort will ultimately lead to success, fostering top-down driven confidence. Individuals scoring low in perseverance seem to give up confidence after experiencing failure despite high effort, reflecting a fixed mindset about their own ability. Supporting this explanation, a previous study found that the top-down driven belief that one's own responses are correct, so-called *choice confidence,* shares the same neural mechanism used to make decisions based on the accumulation of bottom-up perceptual information in the prefrontal and parietal cortices (Gherman & Philiastides, 2015). Our data suggest that persevering people employ this top-down choice confidence when they face a challenge. However, since we do not have any direct measure of the activation of a growth mindset, this interpretation remains speculative. Alternatively, participants' subjective ratings may primarily reflect affective responses to perceived success in the task, rather than intrinsic motivation.

We could not confirm H5 predicting that emotional stability and learning from mistakes would moderate participants' mood state and engagement. Perhaps the feedback about making mistakes was not enough to elicit a negative mood because the task was seen as a game, rather than as personal goal. Interestingly, an unexpected result was a main effect of trait openness on mood and engagement, revealing that individuals scoring higher in openness showed overall greater engagement and more positive mood, reflecting that they were more interested and curious about the RDM.

4.1. Limitations and future directions

We aimed at a systematic manipulation of nominal difficulty in our design, but results showed some dispersion in performance in the easy and moderate conditions, with some participants scoring at chance in these conditions. Future studies could use a staircase procedure to manipulate difficulty and control individual skills to solve the task. We could not confirm that low emotional stability would predict more negative emotion in the difficult task. Using a task more relevant for personal goals, e.g., academic performance, would be an interesting topic to test in further studies. Although sample size was based on a prior power analysis, the number of models we fitted could have inflated the risk of type I error. Therefore, the reported effect should be replicated with larger samples. Future studies could also investigate the intra-individual change in task engagement as function of time and how traits like perseverance modulate this dynamic change.

4.2. Conclusions

Participants reported more positive mood and more engagement in the RDM task when dot movement coherence was high, and they were more confident about their responses. Mood and engagement decreased as the task became more difficult and performance worsened. The most interesting and novel findings were related to individual differences in personality traits and self-regulation strategies. First, high scores in openness were associated with greater task engagement, possibly reflecting curiosity and interest in the task per se. Second, we observed that low levels of perseverance were associated with larger confidence based on bottom-up visual information. However, when the task became very difficult, persevering individuals showed an increase in choice confidence, probably reflecting the belief that they will eventually succeed if they increase effort. We propose that this top-down confidence explains the brain underpinnings of the sustained effort characteristic of trait perseverance.

CRediT authorship contribution statement

Guillermo Recio: Writing – original draft, Visualization, Supervision, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Sebastian Korb:** Writing – review & editing, Validation, Methodology, Formal analysis, Conceptualization. **Angel Blanco:** Writing – review & editing, Writing – original draft, Visualization, Methodology, Formal analysis, Data curation, Conceptualization. **Rafael Valenzuela:** Writing – review & editing, Funding acquisition, Formal analysis, Data curation, Conceptualization. **José Vicente Pestana:** Supervision, Resources, Investigation, Funding acquisition, Conceptualization. **Nuria Codina:** Writing – review & editing, Supervision, Resources, Investigation, Funding acquisition, Conceptualization.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.paid.2025.113395.

Data availability

Data will be shared in osf

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