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The role of intolerance of uncertainty when solving the exploration-exploitation dilemma[1]

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ABSTRACT

When making behavioral decisions, individuals need to balance between exploiting known options or exploring new ones. How individuals solve this exploration-exploitation dilemma (EED) is a key research question across psychology, leading to attempting to disentangle the cognitive mechanisms behind it. A potential predictive factor of performance in an EED is intolerance of uncertainty (IU), an individual difference factor referring to the extent to which uncertain situations are reported to be aversive. Here, we present the results of a series of exploratory analyses in which we tested the relationship between IU and performance in an EED task. For this, we compiled data from 3 experiments, in which participants received the opportunity to exploit different movements in order to avoid a painful stimulus and approach rewards. For decomposing performance in this task, we used different computational models previously employed in studies on the EED. Then, the parameters of the winning model were correlated with the scores of participants in the IU scale. Correlational and cluster analyses, within both frequentists and Bayesian frameworks, did not provide strong evidence for a relation between EED and IU, apart from the decay rate and the subscale "tendency to become paralyzed in the face of uncertainty". Given the theoretical relation between EED and IU, we propose research with different experimental paradigms.

1. Introduction

Successfully addressing changes in the environment is a cardinal characteristic of adaptive responding. This successful adaptation includes the organism's ability to choose between exploiting options with known outcomes (e.g., driving the same way home) and exploring new options (e.g., choosing a new way home). A balance between exploration and exploitation is considered adaptive (see (Kembro et al., 2019) for evidence in non-human animals), with over-exploration or over-exploitation being indicative of maladaptive responding (e.g., anxiety-related disorders or substance abuse Aylward et al., 2019; Browning et al., 2015; Gagne et al., 2020; Kaplan and Friston, 2018;; Smith et al., 2021). How individuals solve this so-called exploration-exploitation dilemma (EDD) is one of the challenges in understanding both adaptive and maladaptive responding (Mehlhorn et al., 2015).

Apart from abuse-related or anxiety-related disorders, the imbalance between exploration and exploitation could prove relevant in illnesses where disabling behavioral patterns are observed. One of these is chronic pain (Vlaeyen and Crombez, 2020). Although protective behaviors (e.g., escape, avoidance) are useful and adaptive in (ongoing) *acute* pain, in the case of *chronic* pain individuals exhibit typically inflexibility in their behavioral patterns, performing activities that lead to the (expected) least pain and avoiding performing different actions, with potentially valued outcomes. This over-exploitation of non-painful behaviors, and under-exploration of other actions, preserves the beliefs of a painful outcome not occurring due to the performance of the behavior, leading to a vicious circle of avoidance's maintenance. In addition, over-exploitation is detrimental for therapies of chronic pain

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that rely on the exposure of individuals to the feared outcome (e.g., a patient that is afraid of breaking her back while bending is asked to bend and lift a heavy load) (Vlaeyen and Crombez, 2020). This type of therapeutic protocols relies on individuals performing actions that they avoid such that their expectation of a feared outcome occurring is challenged (Hollander et al., 2016). Reaching a deeper understanding of the factors that may predict imbalance when solving the EED in pain could prove invaluable towards comprehending both acute and chronic pain, as well as for potentially building relevant prevention treatment protocols.

In this line of research, we have recently conducted 3 laboratory studies in which we tested how healthy individuals balance between exploration-exploitation when their responses could lead to acute pain and/or rewards (Angelos-miltiadis Krypotos et al., 2022). In all experiments, participants were given the opportunity to perform joystick movements towards one of the four corners of a computer screen, a task that was based on the *n*-bandit tasks widely used in the literature (see Fig. 1)(Bouneffouf and Rish, 2014; Daw et al., 2006; Schulz et al., 2020). Each one of the movements was associated with different probabilities of receiving a painful stimulus (Experiment 1) and/or lottery rewards (Experiments 2 and 3). As such, participants were able to explore the different options and learn via experience which movement would lead to the absence of the painful stimulus and the lottery ticket. For analysing our data we fitted different computational models to our data that have been previously used in EED studies (Ahn et al., 2017). Results showed that after initial exploration, participants exploited the option with the lowest chances of receiving a painful stimulus and that participants tended to return to exploration after receiving a painful stimulus. Collectively, our studies provided a new task for solving the exploration-exploitation dilemma, together with some first evidence on how healthy individuals balance exploration-exploitation options when pain outcomes are involved.

A secondary aim of our first 3 experiments was about the potential role of individual differences in performance. If some trait factors could predict over-exploration or over-exploitation in our task, then these factors could inform further research in predicting dysfunctional behaviors in chronic pain. One relevant individual factor for the exploration-exploitation dilemma is intolerance of uncertainty (IU) (Sexton and Dugas, 2009). IU refers to how individuals perceive and respond to unknown, and hence uncertain situations (Birrell et al., 2011; Carleton, 2016a, 2016b). In uncertain situations, individuals with high levels of IU may overestimate the probability of a negative event happening, leading them to exhibit increased avoidance behaviors. As during our EED task participants were not instructed about the contingencies (e.g., actual reinforcement rates), then it could be argued that at the beginning of the task participants likely experience estimation uncertainty related to the probabilistic structure of the environment (Payzan-LeNestour and Bossaerts, 2011). However, with experience the contingencies can be learned, thus decreasing estimation uncertainty and increasing expected uncertainty (also known as irreducible uncertainty or risk) related to the probabilistic structure of the environment (Kobayashi and Hsu, 2017). Basically, in this EED task, over time participants can lower the uncertainty of receiving pain (e.g., learn the probability of pain and select the option with the lowest probability of pain occurrence) but cannot remove the uncertainty of receiving pain all together (e.g. even in the 10 % reinforcement option there is uncertainty of receiving pain). Although initially IU was conceptualized as being close to worry in Generalized Anxiety Disorder (GAD), it is now accepted as a transdiagnostic dimension across mental disorders (Gentes and Ruscio, 2011; McEvoy et al., 2019). Notably, there is an emerging field of research examining behavioral and psychophysiological markers of IU to understand psychopathology (e.g., Morriss and Zuj, 2021; Tanovic et al., 2018).

Arguably, there seems to be a theoretical link between IU and EED. Specifically, when solving the EED individuals often need to deal with incomplete information. In this type of situations, it could be hypothesized that individuals high in IU would tend to exploit familiar behaviors, rather than explore novel actions, a decision that would further increase the uncertainty of the situation. If that would be the case then, we would expect that even in the case of acute experimental pain, there would be a correlation between levels of IU and performance in our pain task, with individuals with higher levels of IU predicting higher levels of exploitation.

In our initial work, we had included the Dutch version of the *intolerance of uncertainty scale* (Helsen et al., 2013), one of the most common scales for evaluating IU, as one in the battery of questionnaires that participants had to fill in. Running correlational analyses for each experiment separately showed no significant correlations between the sub-scales of the IU scale (see Methods for a discussion of the used subscales) and any of the parameters of the winning model. However, there were some potential limitations in our initial analyses. First, each correlation included data of maximum 50 participants. This meant that our statistical power to detect a significant result was low. Second, correlational analyses are only one kind of statistical approaches testing individual differences. Indeed, it has been suggested that given the lack of a computational model for the relation between IU and EDD that would incorporate individual differences in its definition, different statistical analyses may seem appropriate, with none of them being necessarily superior to the other (Steegen et al., 2016). Employing different types of statistical analyses in a larger sample size could prove informative in future confirmatory studies on the relation between IU and the EED.

Here, we present an exploratory reanalysis of our previously collected data in which we try to overcome the above-mentioned limitations. To overcome the limitation of power, we have aggregated data across the different experiments into one, leading to a total sample size of 138 participants. To overcome the limitation of the non-consensus in the appropriate statistical analytic option, we have also analysed the data performing multiple data reduction techniques together with carrying out different statistical analyses within both a frequentist and Bayesian framework. We have also used computational models to analyze our data. In summary, the computational models included a combination of the following parameters. First, punishment and reward sensitivity parameters, which refer to how much participant desire a reward or dislike receiving a punishment. Second, punishment and reward learning rate parameters, which refer to how quickly individuals learn information from previous trials. Third, a lapse rate parameter that is indicative of unexpected responses. Forth, the decay rate parameter that shows how much individuals forget the values of previous unchosen values. Lastly, the noise parameter, also mentioned as 'trembling hand' decisions, is an extension of previous models and encompasses the possibility of random decisions, meaning decisions that are independent of the inferred values for each choice.

2. Methods

2.1. Participants

We collected data of 150 participants, 50 participants for each experiment. However, due to incomplete responses in the task (1 participant), mistakes in testing (1 participant), or incomplete data for the IU scale (10 participants), we ended up with 138 participants (45 in experiment 1, 47 in experiment 2, and 46 in experiment 3), amounting to 138 participants in total (29 males, 109 females, Mean age: 20.81, Standard deviation: 2.99).[2]

Full details about our methodology are described in (Krypotos et al., 2022). Here, we summarize the main experimental procedure across the three experiments.

[2] Please note that in our initial report we had 148 participants in total as the primary analyses referred to the performance in the EED and not the individual differences.

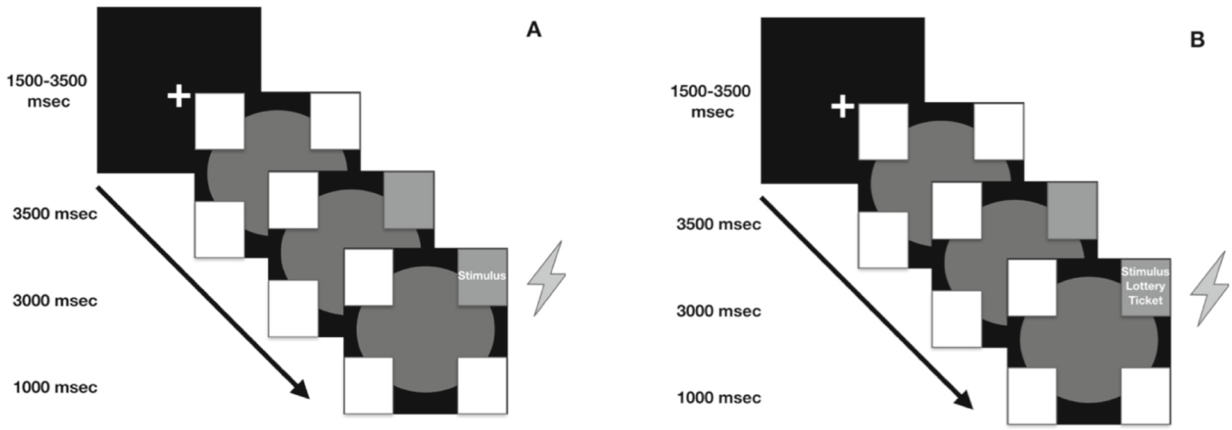

Fig. 1. The two panels depict the trial sequence for Experiments 1 (panel A) and Experiments 2–3 (panel B). See main text for more details.

2.1.1. Stimuli

On each trial across the different experiments, participants encountered four white squares that were presented on each one of the four corners of a computer screen (see Fig. 1). Each square indicated the movement orientation that participants were able to perform (e.g., the top right square indicated that a movement towards the top right could be performed). The squares could be selected by moving a joystick (Logitech Attack 3) towards one of the four square locations. A purple circle was presented in the middle of the screen. An electrocutaneous stimulus of 2 ms duration, delivered via a Digitimer DS7 stimulator, served as the painful stimulation. The word 'lottery ticket' served as the rewarding stimulus for Experiments 2 and 3, with the reward being individually selected from a list of rewards before the beginning of the experiment.

2.1.2. Questionnaires

At least one day prior to the experiment, participants were requested to fill in multiple questionnaires (see Krypotos et al., 2021 for details) using Limesurvey (LimeSurvey Project Team / Carsten Schmitz, 2012). Here we focus only on two scales. First, is the intolerance of Uncertainty Scale, the scale that is used widely for testing IU (Helsen et al., 2013). This scale consists of 27 items with questions such as "When it's time to act, uncertainty paralyses me". Participants can answer each item in a 5-item Likert scale ranging from 1 ("not at all characteristic of me") to 5 ("entirely characteristic of me"). Second, the Neuroticism portion of the Eysenck's Personality Questionnaire (Eysenck and Eysenck, 1975), that we included only to cross-checking our main results.

2.1.3. Ratings

Throughout the experiments, participants provided their evaluations related to each square, the painful stimulus, and the rewarding stimulus. As we are not analysing the ratings here, we do not refer to them anymore. The full report of the rating data can be found in Krypotos et al. (2021) and our online repositories (https://osf.io/32m5p/; https://osf.io/5k3yr/; https://osf.io/pv69j/).

2.1.4. Procedure

The experimental procedure was similar across experiments. In this section, we present the main procedure and between brackets, we include any potential differences between experiments.

The experimental procedure started with participants reading an information brochure and provided informed consent. Then, participants were fitted with the electrodes for the electrocutaneous stimulus on their non-dominant hand. Then, the level of the painful stimulation was individually calibrated on a level that demanded some effort to tolerate, using an adaptive staircase procedure.

Before the beginning of the experiment, participants received verbal and written instructions about the experiments. The experimental task for Experiments 1 and 2 consisted of 300 trials, separated into 2 blocks of 150 trials each. For experiment 3 participants completed 2 more blocks, with a total of 600 trials. In order to acquaint themselves with the task, participants first completed a practice block with 20 trials, where no painful stimulation was administrated (all Experiments) and the lottery tickets did not count in the final scores (Experiments 2 and 3).

For the practice phase of Experiment 1 the instructions were as follows:

"You will soon see 4 squares appear on the screen. Upon seeing the squares, we ask you to move the joystick as fast as possible towards 1 of the 4 squares, as you wish. Once you have moved the joystick, the selected square will light up. After that, you will either receive an electrical stimulus or nothing at all. We will start the task with a practice phase. In this phase you will see on the screen whether you will receive an electrical stimulus, but no real stimulus will be given yet. After the practice phase we will move on to the main task." For the practice phase of Experiments 2 and 3 the instructions were as follows:

"You will soon see 4 squares appear on the screen. Upon seeing the squares, you will have to move the joystick as fast as you can towards 1 of the 4 squares, as you wish. Once you move the joystick, the chosen square will light up. After that you will either receive an electrical incentive, or 1 lottery ticket, or both, or nothing at all. We will start the task with a practice phase. In this phase you will see on the screen if you would receive an electrical incentive or lottery tickets but no real incentive or lottery ticket will be given yet. After the practice phase we will move on to the main task". For the main phase of Experiments 1 and 2 the instructions were as follows: "This was the end of the practice phase. Now the actual experiment begins. The main task consists of 2 parts with a short break between each part." Lastly, for the main phase of Experiment 3 the instructions were as follows: "This was the end of the practice phase. Now the actual experiment begins. The main task consists of 4 parts with a short break between each part."

Each trial began with the presentation of a fixation cross that participants were requested to look at. After the disappearance of the fixation cross, participants were instructed that they could move the joystick to any of the squares presented on the screen (time limit: 3000 msec). In case the participant performed the movement, the selected square turned blue and remained on screen for 3000 msec. In case of a painful stimulus, the electrocutaneous stimulus was administrated and the word 'stimulus' appeared simultaneously on screen for 1000 msec. The intertrial intervals were jittered, ranging from 1500 to 3500 msecs. For Experiments 2 and 3 the word 'lottery ticket' appeared in case of a rewarding stimulus. Importantly, each square was associated with a different mean probability of a painful stimulation (for all Experiments) and/or reward (for Experiments 2 and 3). Specifically, for experiment 1, the following punishment probabilities were programmed: 10 %, 30 %, 50 %, and 70 %. For Experiments 2 and 3, the punishment/reward probabilities were the following: 10 %/90 %, 30 %/70 %, 50 %/50 %, and 70 %/30 %.

At the end of each block, participants evaluated the four squares, the electrocutaneous stimulus, and the lottery tickets (Experiments 2 and 3).

3. Statistical analyses

All the analyses were performed in the combined data set across the different experiments. We used the first two blocks of each experiment. Although Experiments 1 and 2 consisted of only 2 blocks each, Experiment 3, consisted of 4 blocks, with the choice-outcome contingencies in the last two blocks changing. As such, we have decided to use only the first 2 blocks of this experiment as these two blocks were mostly similar to those of Experiments 1 and 2. How to quantify the EED is a matter of debate with different studies following different approaches. As exploitation is sometimes defined as repeating the same behavior and exploration as selecting a different one, the EED could be quantified simply as switch/no-switch behavior across trials (Byrne et al., 2022). However, this definition ignores behavior across time. For example, a continuous switching between two options would be defined as exploration although if someone considers performance per two trials then the data would suggest that this is purely exploitation (i.e., continuous switching between two options). To overcome this, different computational models have been suggested in the literature (see Ahn et al., 2017) that consider, among others, time as well. Our approach for selecting the winning computational model is described elsewhere (Krypotos et al., 2021). In summary, for each data set, we fitted 5 models using the hBayesDM (Ahn et al., 2017) package for R (R Core Team, 2018). Within the package, the models are named as follows: bandit4arm_2par_lapse, bandit4arm_4par, bandit4arm_lapse, bandit4arm_lapse_decay, and bandit4arm_singleA_lapse, which refer to the lapse decay model (Niv et al., 2015), the 4-parameter lapse model (Seymour et al., 2012), and the 2 parameter lapse model (Aylward et al., 2019). The main variables across the models are punishment and reward sensitivity, punishment, and reward learning rate. The sensitivity parameters show how much individuals expect to like a reward or dislike a punishing stimulus. The parameters referring to the learning rate show how fast individuals acquire information from past trials. Some models also include a lapse and a decay parameter. The lapse parameter is indicative of unexpected responding. The decay rate parameter shows the degree participants forget the values of the different options the more they are not choosing them. We performed the model comparison by using the leave-out-one information criterion (LOOIC) (see Vehtari, Gelman, & Gabry, 2017 for details), with the winning model being the model with the lowest LOOIC information value. Then, the model parameters for the winning model were accessed by running separate Markov Carlo Monte Chains (MCMCs) and using the R-hat criterion (Gelman, Rubin, & others, 1992), with values below 1.1 being suggestive of good chain convergence. Lastly, the parameters were standardized and were subsequently separated for each of the factors of the IU scale. For interested readers, we have included descriptions of the choice data in the Supplementary material.

The factor structure of the IU scale is a matter of debate (Id et al., 2019). Although most studies would employ a 1 factor solution, reports on the factor consistency of the IU scales have shown that there could be possible 2, or 4 different factors.[3] In order to account for the possible subfactors, we considered factors from the 2 and 4 item solution. For the 2-factor solution these are: 1) uncertainty has negative behavioral and self-referent implications, and 2) uncertainty is unfair and spoils everything. There are two 4-factor solutions available. The first one has the following factors: a) desire for predictability; (b) tendency to become paralyzed in the face of uncertainty; (c) tendency to experience distress in the face of uncertainty; and (d) inflexible uncertainty beliefs. The second 4-factor solution has the following factors: (a) desire for predictability, (b) uncertainty paralysis, (c) uncertainty distress, and (d) inflexible uncertainty beliefs. Lastly, we have used the short version of the IU scale (Carleton et al., 2012). The distribution of all subscales is included in the supplementary material.

The parameters of the winning model were correlated with the IU scale and its subscales using separate Spearman correlations, as well as Bayesian correlations using the BayesFactor R package (Morey and Rouder, 2021). As multiple correlations were run, we have decided to reduce our alpha level to 0.001 to reduce the possibility of a false-positive result. Also, we considered Bayes factors above 10 indicative of strong evidence for the data coming from the alternative, compared to the null hypothesis (denoted with BF10), and the reversed for values below 0.1 (Jonathon et al., 2018). Lastly, BF10 values between 0.1 and 10 indicate inadequate evidence for any of the tested hypotheses.

Apart from using correlation analyses, the frequentists and Bayesian analyses, we have followed a second analytic technique that is often used in exploring individual differences in conditioning research. This is cluster analyses, or latent growth curve modeling when the factor of time is considered. This data-driven technique includes the grouping of participants' responses according to their similarity into different groups. For doing that we standardized the values of the parameter's values of each winning model and then created clusters. Then, we ran frequentists and Bayesian analyses of variances (ANOVAs) with the group allocation and the IU scale factors as dependent variables. All Bayesian analyses were run with the BayesFactor as well using the default options of the R package, with similar settings also used in other software (e.g., JASP; Jonathon et al., 2018).

4. Results

The winning model had the following parameters: reward learning rate, punishment learning rate, reward sensitivity, punishment sensitivity, noise, and decay rate. For details on the model comparison, as well as the posterior predictive checks, please see Krypotos et al., (2021). The pattern correlations of each parameter with the different subscales revealed no significant correlations (see Fig. 2) apart from the decay rate and the subscale "tendency to become paralyzed in the face of uncertainty". Higher values on this subscale were associated with a greater tendency to forget the values of the different options the longer they had not been chosen. In other words, higher values on this subscale were associated with sticking to a particular option and subsequently forgetting the outcome information of the other options. There were some Bayes factors above 10, suggesting strong evidence from the data coming from the alternative compared to the null hypothesis (see Table 1) but these results may be interpreted with caution given that those results in only one case agree with the results of the frequentists results.

The cluster analyses championed a 3-cluster solution. The separate ANOVAs between the clusters and the IU factors showed no significant relationship for intolerance of uncertainty or any of the tested factors, with similar Bayesian results (Table 2). Collectively, none of the results

[3] We do not consider the report by Freeston et al. (1994) who found a 5-factor solution rs the authors explicitly mention that their factor analysis was performed to show that the items of scale covary rather than propose different subscales.

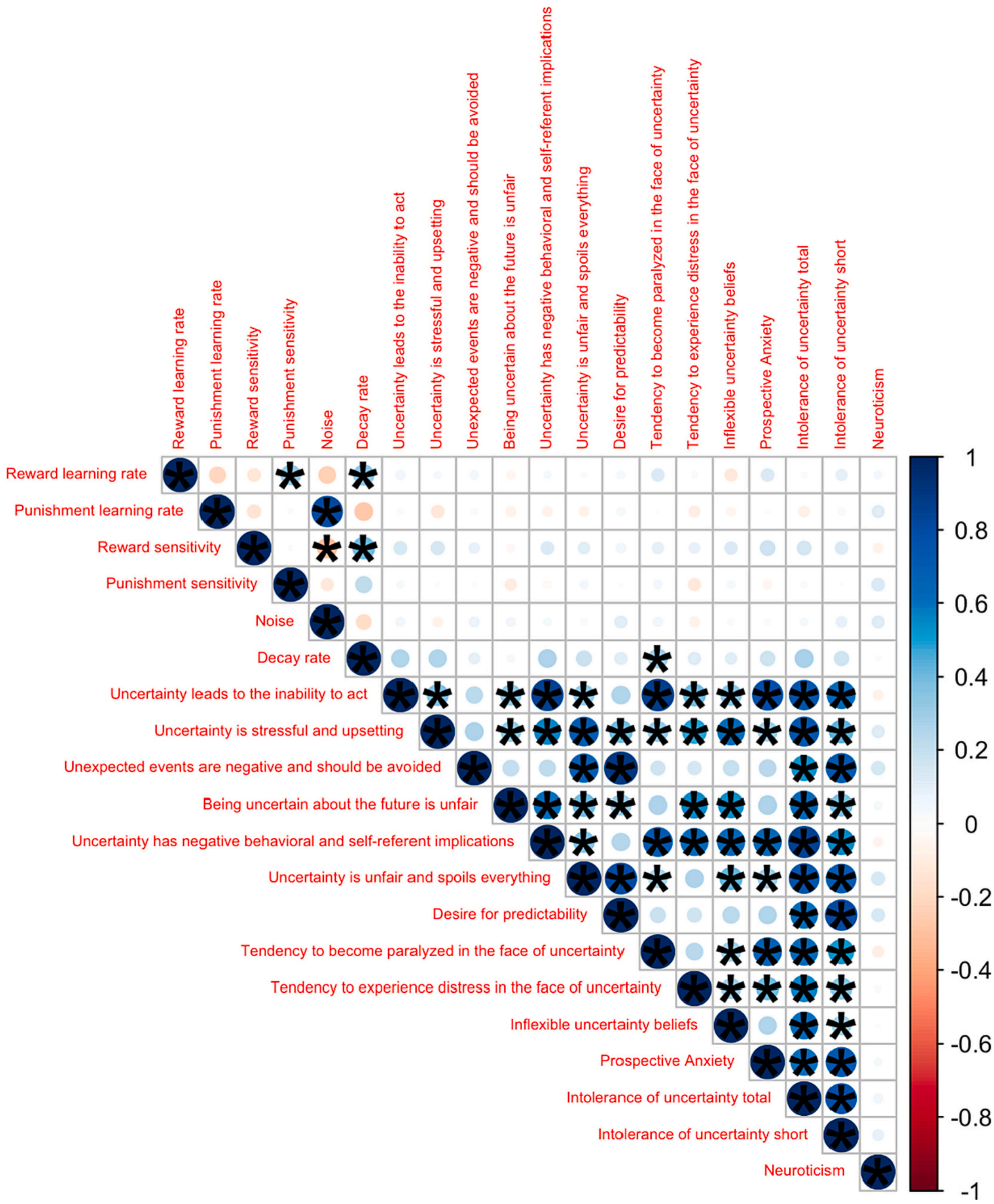

Fig. 2. *A graphical* display of a correlation matrix between the model parameters (i.e., reward learning rate, punishment learning rate, reward sensitivity, punishment sensitivity, noise, and decay rate) and each one of the subscales of the Intolerance of Uncertainty scale for the different suggested factors (uncertainty leads to the inability to act, uncertainty is stressful and upsetting, unexpected events are negative and should be avoided, being uncertain about the future is unfair, uncertainty has negative behavioral and self-referent implications, uncertainty is unfair and spoils everything, desire for predictability, tendency to become paralyzed in the face of uncertainty, tendency to experience distress in the face of uncertainty, inflexible uncertainty beliefs, intolerance of uncertainty total. Significant values are visualized with the star symbol. Red color indicates a positive correlation whereas a blue color a negative correlation. The more blue or red the color the higher the correlation.

above provided strong evidence that any of the subfactors in the IU correlate with performance in our EED task.

5. Discussion

In this exploratory study, we studied whether IU influenced the EED dilemma when participants have the opportunity to avoid receiving a painful stimulus or to approach a rewarding stimulus (Experiments 2 and 3). For that, we carried out different types of analyses within both the frequentists and Bayesian inferential framework. For quantifying performance, we relied on computational models used in the literature, models that can be used for decomposing performance into distinct mathematical parameters. Collectively, none of the results provided any conclusive evidence for a relation between IU, or neuroticism, and performance in EED task.

In this study we have used an exploratory approach, using different statistical models and inferential approaches. None of them was able to provide strong evidence that performance in our EED task correlated with the IU scale. The only significant correlation, with strong evidence

Table 1
Table of Bayes factors (BF10) for the correlation between the different parameters of the winning model and the subfactors of the IU scale.

	Reward learning rate	Punishment learning rate	Reward sensitivity	Punishment sensitivity	Noise	Decay rate
Uncertainty leads to the inability to act	0.30	0.20	0.57	0.20	0.23	21.47
Uncertainty is stressful and upsetting	0.21	0.35	0.51	0.20	0.20	8/60
Unexpected events are negative and should be avoided	0.20	0.20	0.21	0.21	0.30	0.93
Being uncertain about the future is unfair	0.22	0.23	0.22	0.20	0.40	0.24
Uncertainty has negative behavioral and self-referent implications	0.20	0.21	0.57	0.20	0.21	14.82
Uncertainty is unfair and spoils everything	0.20	0.22	0.25	0.26	0.35	3.27
Desire for predictability	0.21	0.21	0.20	0.21	0.28	1.09
Tendency to become paralyzed in the face of uncertainty	0.54	0.20	0.35	0.20	0.29	114.30
Tendency to experience distress in the face of uncertainty	0.20	0.30	0.25	0.27	0.20	0.87
Inflexible uncertain beliefs	0.98	0.20	0.45	0.26	0.28	0.42
Prospective Anxiety	0.60	0.20	0.79	0.20	0.20	1.70
Neuroticism	0.22	0.34	0.41	1.75	1.54	0.20
Intolerance of uncertainty short	0.35	0.20	0.33	0.20	0.22	3.89
Intolerance of uncertainty total	0.20	0.22	0.41	0.20	0.20	27.91

Table 2
Table with frequentists and Bayesian results for each tested factor for the intolerance of uncertainty scale.

Factor name	Statistical results
Uncertainty leads to the inability to act	$F(2, 135) = 1.71, p = .18, \eta_G^2 = 0.02$; $BF_{10} = 0.497$
Uncertainty is stressful and upsetting	$F < 1$; $BF_{10} = 0.35$
Unexpected events are negative and should be avoided	$F < 1$; $BF_{10} = 0.307$
Being uncertain about the future is unfair	$F < 1$; $BF_{10} = 0.188$
Uncertainty has negative behavioral and self-referent implications	$F(2, 135) = 1.16, p = .32, \eta_G^2 = 0.02$; $BF_{10} = 0.372$
Uncertainty is unfair and spoils everything	$F(2, 135) = 1.30, p = .28, \eta_G^2 = 0.02$; $BF_{10} = 0.393$
Desire for predictability	$F < 1$; $BF_{10} = 0.294$
Tendency to become paralyzed in the face of uncertainty	$F(2, 135) = 2.28, p = .11, \eta_G^2 = 0.03$; $BF_{10} = 0.639$
Tendency to experience distress in the face of uncertainty	$F < 1$; $BF_{10} = 0.288$
Inflexible uncertain beliefs	$F < 1$; $BF_{10} = 0.162$
Prospective anxiety	$F < 1$; 0.22
Neuroticism	$F(2, 135) = 1.74, p = .179, \eta_G^2 = 0.025$; $BF_{10} = 0.27$
Intolerance of uncertainty short	$F < 1$; $BF_{10} = 0.32$
Intolerance of uncertainty total	$F(2, 135) = 1.38, p = .26, \eta_G^2 = 0.02$; $BF_{10} = 0.527$

also in terms of Bayes factors, was the correlation between the "Tendency to become paralyzed in the face of uncertainty" and the "decay rate."[4] Although this could provide some first evidence for further research in this factor, this result should be interpreted with caution given that this is an exploratory study and this was the only significant result.

There are at least three different explanations for explaining the absence of concrete evidence for a relation between performance in the EED and the IU scale. First, a source of lack of variability could be the task used, as it included highly aversive stimuli and a paradigm in which it was relatively easy for participants to reach maximum performance. In different articles, it has been suggested that such *strong* paradigms may not be fit for exploring individual differences (Beckers et al., 2013; Lissek et al., 2006). Future studies studying individual differences could use multiple stimuli on each trial, something that could increase uncertainty of the chosen outcome. This increased uncertainty could increase the variance in responses and subsequently give room for detecting individual differences in decision-making (Beckers et al., 2013; Holscher et al., submitted). In addition, the task had a low level of uncertainty, as the stimuli and probabilities were fixed, something that may have resulted in low levels of exploration and as such low variability in the data. Future tasks could increase the level of uncertainty, with for example different stimuli presented across trials, may increase such uncertainty and lead to more exploratory behaviors, and as such more variability in the data (Morriss et al., 2019, 2021;Walker et al., 2021). Lastly, our findings could point to the absence of a relation between IU and EED, at least on how these variables were operationalized here.

Apart from the task used that may not be appropriate to shed light on potential individual differences, another limitation could refer to the used questionnaire for evaluating the IU trait. Although we have used the full version of the IU scale, alternative versions have been suggested in the literature (e.g., in Sexton and Dugas, 2009). In addition, even with the version we have used, different subscales have been detected in different articles. Here, we have used the different subscales in an attempt to detect any potential relationships. However, that not all researchers are using the same factors for the said questionnaire. In future research, it is important that researchers who examine the different subscales/factors also report the results from the full IU scale as well for transparency. Lastly, a limitation of our study could be that we did not build a novel computational model that would incorporate intolerance of uncertainty in its definition. We hope that future studies could do that inspired by the present findings together with the dataset we have provided already.

All in all, in this exploratory study we did not find strong evidence for a relation between IU, or neuroticism, and performance in an exploration-exploitation task. Given that theoretically the IU and EDD seem to overlap, more research attempting to disentangle these two constructs seems warranted.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ijpsycho.2022.08.001.

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[4] We note that the divergence between the frequentists and Bayesian results is not uncommon, something that addresses the differences in inference between these two approaches (see Krypotos et al., 2017a, 2017b for relevant discussions).

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