Multimetric behavioral profile and psychological traits

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37 **Abstract**

38 External sources of information determine human actions. However, psychological traits (PTs),
39 considered internal variables, also play a crucial role in decision-making. PTs are stable across time and
40 contexts, and they define the set of behavioral repertoires that individuals express. Here, we explored
41 how multiple metrics of adaptive behavior under uncertainty related to several PTs. Participants solved a
42 multiple baseline reversal-learning task with volatile contingencies, from where we characterized a
43 detailed behavioral profile based on a wide variety of measurements from their response sequences. We
44 then tested the relationship between the multimetric behavioral profile and a wide range of self-reported
45 psychological questionnaires. The PT measurements were based on the Hierarchical Taxonomy Of
46 Psychopathology (HiTOP) model. We found that the learning curves alone predicted important
47 differences in the PTs, and task response times. Similarly, the behavioral profile configurations
48 predicted the PTs, and could be used as a ‘fingerprint’ to identify participants with a high certainty level.
49 We discuss how this characterization could contribute to constructing a better nosological classification.

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61 **Keywords:** behavioral phenotypes, psychological traits, reversal-learning, Bayesian learning

62 **Introduction**

63 Humans continuously adapt their actions to a changing environment. They do so in particular and unique
64 ways associated with each individual (Roberts, 2009;Sauce and Matzel, 2013;Byrom and Murphy,
65 2018). Decisional strategies adopted by persons depend on internal (individual/genetic differences) and
66 external (decision features, situational and environmental factors) factors (Appelt et al., 2011;Sauce and
67 Matzel, 2013). Thus, a current topic of intense research is the study of how psychological traits (PTs;
68 *v.gr.*, any domain of personality and cognitive functions) influence decision-making. PTs can be easily
69 assessed through self-reporting questionnaires, and these traits persist over days, years, and even
70 decades (Harris et al., 2016).

71 Analysis of the origin and classification of individual differences has led to a deeper
72 understanding of human behavior (Byrom, 2013;Griffiths et al., 2014). Individual differences manifest
73 as time-consistent features (traits) or as time- and context-dependent features (states). Recent evidence
74 suggests that people use distinct sources and amounts of information to update their task-solving
75 strategies, particularly in volatile environments (Behrens et al., 2007;Hilbig, 2008;Michalkiewicz and
76 Erdfelder, 2016). The adaptive mechanisms that deal with uncertainty have been linked to specific
77 genes, brain circuits, and PTs (Allport, 1961;Lewis and Kim, 2009). Thus, maybe not surprisingly, PTs
78 have been found to predict some differences in contingency learning and goal-directed behavior (Msetfi
79 et al., 2015;Gillan et al., 2017). For example, anxious individuals learn poorly in uncertain environments
80 (Browning et al., 2015); depressive traits predict impairments in context processing (Msetfi et al., 2005);
81 people diagnosed with obsessive-compulsive disorder (Gillan et al., 2011) and with
82 schizotypy/schizophrenia (Le Pelley et al., 2010;Morris et al., 2013;Morris et al., 2018) exhibit impaired
83 goal-directed behavior and associative learning capacities (Haselgrove and Evans, 2010). Therefore,
84 self-reported psychological measurements can be linked to differential behavioral manifestations (see
85 *v.gr.* (Griffiths et al., 2019).

86 Using a series of forced-choice and reversal-learning tasks, we have recently shown how humans
87 (and mice) exhibit idiosyncratic but stable choice biases across tasks and days (Treviño et al.,
88 2020;Trevino et al., 2021). These findings revealed that at least a portion of the biases observed derived
89 from internal variables that were entirely independent of the sensory and contextual elements involved
90 in the tasks. The consistency in the behavioral phenotypes extracted from individuals when solving our
91 tasks made us wonder whether these profiles could inform psychological traits, mental disorders, and
92 maybe even psychopathologies (Neuringer, 2002).

93 Here, we explored whether multiple behavioral metrics (*i.e.*, an extensive behavioral profile) of
94 neurotypicals solving a perceptual task predicted individual differences in their PTs. We first assessed
95 the PTs with questionnaires covering six specters from the Hierarchical Taxonomy Of Psychopathology
96 (HiTOP) model. The HiTOP is an empirically driven, quantitative classification system that constructs
97 the notion of psychopathological syndromes based on co-variation of symptoms (Kotov et al., 2017).
98 We choose the HiTOP because it simplifies the idea of PTs into wide, hierarchically arranged specters:
99 thought disorder (e.g., schizotypal personality), somatoform (e.g., somatization disorder), internalizing
100 (e.g., state and trait anxiety), disinhibited externalizing (e.g., impulsivity), detachment (e.g., anhedonia),
101 antagonistic externalizing (e.g., narcissism). Next, we tested the same individuals in a reversal-learning
102 task with volatile contingencies and quantified multiple behavioral features when solving the task. We
103 found that schizotypy and anxiety traits exhibited learning differences in reward and volatility
104 estimations both in stable and randomized rewarding conditions. In contrast, somatoform traits exhibited
105 differences in volatility estimates only in stable rewarding conditions. Using multiple linear regression
106 (MLRM) analyses, we confirmed that the behavioral profiles predicted the PTs above chance levels and
107 classified the participants. These significant relationships imply that the behavioral responses when
108 solving the reversal-learning task contained information about the PTs, and predict the subjects' identity.

109 Our results provide a simple yet powerful example of how objective psychometric and psychological
110 measurements explain potential differences in the more broadly used neuropsychological scales.

111

112 **Materials and Methods**

113 **Participants.** We conducted experiments in a total of 152 neurotypicals (72 women and 80 men; age
114 range (yr.): 17-40, mode: 19; with approval from the ethical committee of our institution: ET092018-
115 271). Most participants were dextral ($\geq 85\%$), without visual impairments, diagnosis of neurological
116 disorders, or drug abuse history. We gave all participants written instructions on how to respond to the
117 questionnaires and solve the task. Before being tested, participants performed a brief pre-training phase
118 to obtain 20 consecutive correct trials using the reversal-learning task (described below).

119
120 **Assessment of psychological traits (PTs).** We characterized participant's PTs based on HiTOP specters
121 (Kotov et al., 2017) by applying a series of paper (*i.e.*, printed forms) and electronic questionnaires
122 (using Google Forms; self-report) with no time limit. We focused on the following specters: 1) Thought
123 Disorder: Schizotypal Personality Questionnaire (SPQ); seventy-four items (Raine, 1991); 2)
124 Somatoform: Othmer and DeSouza Test for Detection of Somatization Disorder; seven items (Othmer
125 and DeSouza, 1985); 3) Internalizing: State and trait Anxiety Inventory (STAI; split by two subscales);
126 forty items (Spielberger et al., 1970); 4) Disinhibited Externalizing: Plutchik Impulsivity Scale, EI;
127 fifteen items (Plutchik and Van Praag, 1989); 5) Detachment: Revised Physical Anhedonia Scale
128 (RPhA); sixty-six (Chapman et al., 1976); 6) Antagonistic Externalizing: Hypersensitive Narcissism
129 Scale, (HSNS); ten items (Hendin and Cheek, 1997). A psychologist carried out the HiTOP testing,
130 employing validated scales for Spanish-speaking people (García et al., 2002). We also included some
131 socio-demographic questions (gender, age, native language).

132
133 **Analysis of PTs.** We made histograms of the normalized scales from the PTs from a group of
134 participants and calculated the distribution fits using normal density functions. We then took the mean

135 (μ) and standard deviation (σ) as distribution parameters. We employed a linear regression model to
136 compare PTs estimated using paper and electronic questionnaires. From these fits, we extracted the
137 slope (m), coefficient of determination (R^2), root-mean-squared error (RMSE), and the P -value for the
138 F -test on the model (which tests whether the model fits better than a constant term). We explored the
139 possibility that an underlying ‘latent’ structure explained the average responses from the seven HiTOP
140 specters (e.g., (Gillan et al., 2016). For that, we employed a factor analysis model (with three factors
141 max. given the number of observed variables) using maximum likelihood estimation (MLE).

142

143 **Reversal-learning task.** We adapted a two-alternative match-to-sample task to include a second forced-
144 choice phase independent of the first choice. We have described this task in detail previously (Trevino et
145 al., 2021). Briefly, participants sat upright in front of a computer monitor as we used a joystick to record
146 their choices (Thrustmaster 2960623 USB Joystick). The visual stimuli (416 x 300 pixels; visual angle:
147 $7^\circ \times 5^\circ$) consisted of two pictures displayed simultaneously on a single 27-inch computer monitor (Dell
148 P2414H; ~ 60 cm away from the participants’ eyes). These two images had low semantic attributes, as
149 validated before (Trevino et al., 2020). We manipulated the task difficulty by generating distracter
150 images (*i.e.*, the S^Δ , delta, or non-rewarded stimulus) by using pictures with different similarities (SIM)
151 relative to the sample stimulus (*i.e.*, the S^D , discriminative, or rewarded stimulus). Participants had to
152 press the joystick towards one direction indicated by instructive arrows projected on the screen’s center
153 to solve the task. Choice regions corresponded to 5% of the total search space. The response times (RT,
154 in s) were quantified and stored as the interval between the visual stimuli’ presentation and when
155 participants put the joystick in one of the available response regions. The participants had to let the
156 joystick return to its baseline position after choosing. They had to make a visual choice during the first
157 forced-choice phase based on identifying the side (left or right) where the S^D was projected for 1 s. Two

158 left and right white arrows appeared at the center of the display after the visual stimuli were projected.
159 The possible response options were shown by these arrows and stayed on the screen until the participant
160 replied. Next, the SD was projected at the center of the screen for 750 ms or 3 s, respectively, depending
161 on whether the participant responded correctly or incorrectly (*i.e.*, a 1:4 relationship in the waiting
162 intervals). During the second forced-choice phase, two white arrows at the center of the screen pointing
163 to the upper right and left corners indicated the two response options. Here, we reinforced random side-
164 choices (using balanced randomly permuted locations) or left or right side-choices (Trevino et al.,
165 2020;Trevino et al., 2021). The waiting intervals that we employed after participants responded
166 reinforced particular side choices: 750 ms after correct side-choices and 3 s after incorrect side-choices.
167 Thus, the implicit motivation for solving the task was to discriminate correctly (phase 1) and choose the
168 correct side (phase 2) to finish the task promptly. We switched the contingencies for the second choice
169 every 60 trials for 12 blocks/day. All our projection and analysis software was written in (MathWorks,
170 Inc.; Natick, USA) using the Psychophysics Toolbox extensions (PTB-3).

171

172 **Multimetric behavioral profile.** We used a training paradigm with contingencies that favored either
173 random or side-choices, and participants selected the left or right sides during the 2nd side-choice phase
174 of the reversal-learning task (Trevino et al., 2020). Next, we implemented a detailed analysis of these
175 side-choices, as described before (Trevino et al., 2021). Briefly, we took the block-averaged choice
176 records from each participant (y) and fitted them with linear regressions from where we quantified the
177 slopes (m). We also adjusted mono-exponential curves with the form:

$$178 \quad y = \lambda - (y_0 \cdot e^{-\tau x}) \quad (\text{Eq. 1})$$

179 where λ corresponds to the maximum average performance achieved during the block, y_0 is the initial %
180 Correct responses (a free parameter in the fitting procedure), x are the trials within the block, and τ is the

181 rise constant, equivalent to the learning rate constant in associative learning models such as Rescorla and
182 Wagner (1972).

183 Using a Bayesian learning (BL) algorithm, we estimated the reward (r) and volatility (v)
184 probabilities given the history of trial outcomes (rewards) (Behrens et al., 2007; Trevino et al., 2021).
185 The BL constitutes a Markovian Decision Process (MDP; (Sutton and Barto, 1998)) which means that a
186 choice made at a particular trial depends on the information the agent had from the previous trial. Thus,
187 the BL algorithm computes a three-dimensional density function of r , v , and k (the rate of change of v)
188 for every trial. r (or v) is a weighted mean of the marginal distribution integrated by v (or r) and k . A
189 complete breakdown of the BL equations and methods can be found in the original publication's
190 supplementary material by Timothy Behrens and colleagues (Behrens et al., 2007).

191 To assess overall choice biases, we used the stationary (Shannon) entropy:

$$192 \quad H(\text{Response side}) = -\sum_{i=1}^2 P(s) * \log_2[P(s)] \quad (\text{Eq. 2})$$

193 where s is the response side (left or right).

194 To measure the level of unpredictability of the transitions between consecutive choices (Shiferaw et al.,
195 2019), we measured the transition entropy for side-choices as follows:

$$196 \quad H(\text{Response side} | \text{prior response side}) = -\sum_{i=1}^2 P(s_i) \sum_{j=1}^2 P(s_i | s_{i-1}) * \log_2[P(s_i | s_{i-1})] \quad (\text{Eq. 3})$$

197 where s_i is the response side (left or right), and s_{i-1} is the prior response side (left or right). These entropy
198 values ranged between 0 and 1.

199 We applied multiple linear regression models (MLRM) to explore the relationship between
200 behavioral attributes extracted from the reversal-learning task and the PTs (Chamorro et al.,
201 2017; Trevino et al., 2020).

202

203 **Statistical analysis.** We used t-tests, non-parametric tests, and Kolmogorov-Smirnov (KS) tests for
204 group and distribution comparisons. As a reference to determine the significance of the MLRM
205 regression coefficients, we created surrogate data sets ($n = 1000$) using random permutations of the
206 predictors, as previously described (Chamorro et al., 2017; Trevino et al., 2021). We reduced the
207 regression coefficients' space into three dimensions (3D) using principal component analysis (PCA). We
208 illustrate our group data as averages $\pm$ S.E.M. with a significance set at $P \leq 0.05$. The number of
209 participants used for each task's analysis is represented inside parentheses in the corresponding figure
210 panels.

211

212 **Results**

213 **Assessment of psychological traits through self-report questionnaires**

214 We first characterized the psychological traits (PTs) from 111 neurotypicals using electronic
215 questionnaires based on seven HiTOP specters (Kotov et al., 2017); see **Methods**). Frequency
216 histograms and their Gaussian fits are illustrated in **Figure 1A**. We validated the usage of such
217 electronic surveys on another group of 41 naïve participants by contrasting the estimated traits through
218 electronic surveys relative to conventional paper (*i.e.*, printed) questionnaires (**Figure 1B**). As expected,
219 all comparisons exhibited strong positive correlations and coefficients of determination (R^2 ; **Figure 1C**),
220 with the strongest electronic/paper similarities when comparisons involved the same trait (slopes and R^2
221 from paired variables in **Figure 1D**). Given the high correlations across traits, we explored the
222 possibility that some of these specters shared some underlying mechanisms. We performed factor
223 analysis using the average responses from the seven questionnaires. The two- and three-factor analyses
224 revealed distinctive trait compositions (two-factor analysis | F1: low anhedonia; F2: high anhedonia;
225 three-factor analysis | F1: low anhedonia and impulsivity, which are linked to some neuropsychiatric
226 disorders (Houeto et al., 2016); F2: low anhedonia with high impulsivity and anxiety trait, where
227 anhedonia has been associated with transitions between anxiety and depression (Winer et al., 2017); F3:
228 high anhedonia and somatoform; **Figure 1E**). This result suggests that some of the PTs shared an
229 underlying correlative structure. Hence PTs were not entirely independent from each other.

230

Figure 1 | Assessment of psychological traits with the HiTOP scale. (A) Frequency histograms for seven normalized traits, with their Gaussian fits for electronic assessments made in 111 participants. Last panel shows box-and-whiskers plots (box: 25th and 75th quantiles; whiskers: 5th and 95th percentiles). (B) Validation of the measurement of the HiTOP dimensions comparing electronic vs. paper printed questionnaires. Red lines are linear regressions. (C) List of the seven traits with the slopes (m), coefficients of determination (R^2), and P values from the linear regressions shown in panel B. (D) Strong consistency for electronic/paper assessments revealed by pairwise comparisons of normalized scales using the linear regression slopes (top panel) and R^2 (bottom panel) Empty squares correspond to n.s. interactions (*i.e.*, the model can be represented as a constant term). (E) two- (pie charts on top) and three- (pie charts on bottom) factor analysis on the seven specters' average responses. Color codes indicate the constitution of specters for each factor. Number of subjects in parenthesis.

Multimetric behavioral profiles extracted from a reversal-learning task

Once we characterized their PTs, we took the original 111 participants and tested their discriminative and adaptive responses when solving a multiple reversal-learning task. We used a two-alternative match-to-sample task, which allowed us to measure discrimination performance (1st visual choice) and side-choices (2nd forced-choice) during two sequential phases within each trial (see **Methods**; **Figure**

250 **2A**)(Trevino et al., 2020;Trevino et al., 2021). We controlled task difficulty for the 1st visual choice
251 using linear mixtures of the S^A and S^D images leading to different degrees of stimulus similarity (SIM;
252 using Matlab function ‘imlincomb’, with $k = 0.8-1$, **Figure 2B**). For the 2nd forced side-choice, we used
253 variable or stationary rewarding contingencies by reinforcing: i) random, ii) left-only, or iii) right-only
254 sequences. In this task, reward involved waiting for a shorter interval coupled with a green feedback
255 screen (**Figure 2C**; see **Methods**). The training blocks were arranged so that participants underwent all
256 possible transitions (**Figure 2D**).

257 Visual choices depended on stimulus discriminability ($F = 26.8$, $P < 0.001$), with performance
258 dropping when $k \rightarrow 1$ (logistic fit (Trevino et al., 2018): $y_{\max} = 0.35$, $\beta = 60.74$, $x_{50} = 0.96$, **Figure 2E**).
259 Optimal performance in volatile tasks involves combining a dynamic adjustment of evidence’s
260 weighting with prior expectations (Behrens et al., 2007;Lawson et al., 2017). Because our task involved
261 a sequence of two choices within each trial, we explored for sequential effects, but found none ($F =$
262 4.17 , $P = 0.06$), with the side-choices following a random process (rnd, binomial distribution; caramel-
263 brown; $F = 0.35$, $P = 0.55$; **Figure 2F**), fully independent of stimulus discriminability ($F = 1.26$, $P =$
264 0.28 ; **Figure 2G**). Next, we quantified a moving average of the participants’ % correct side-choices
265 (blue line corresponds to group averaged choices, span = 40 trials, **Figure 2H**). As expected,
266 participants exhibited various learning rates based on how they used the feedback information (Pulcu
267 and Browning, 2017;Trevino et al., 2021). We grouped the learning curves by reinforcement conditions
268 and found no net left vs. right bias (Kruskal-Wallis multi-comparison test, $P < 0.001$; **Figure 2H**). We
269 also took the block-averaged choice records from each participant and fitted them with linear regressions
270 and mono-exponential curves. We extracted the corresponding slopes (m), rising taus (τ), and peak
271 values (λ ; not illustrated;(Trevino et al., 2021). We also quantified the participants’ response times (RT,
272 in s) for visual and side-choices. To summarize: the lack of sequential effects in this task allowed us to

make a robust characterization of discriminative capacities and adaptive responses to volatile contingencies separately.

Figure 2 | Behavioral profiles of participants solving a reversal-learning task. (A) Drawing of our experimental apparatus. (B) Variable discrimination difficulty by linear mixtures of two source images. (C) Stimulus time-line of the reversal-learning task (see **Methods**). (D) Time-line depicting the experimental contingencies. (E) Visual psychometric performance. (F) The 1st choice did not produce sequential effects for the 2nd choice, which followed a random binomial process (caramel-brown distribution). (G) Average %correct side-choice (2nd choice) is fully independent from stimulus discriminability. (H) Average %correct side-choice records (2nd choice, blue line), with left (vanilla yellow background), right (flax yellow background), or volatile (*i.e.*, random; empty background) reinforcements. (I) Block averaged learning curves associated with the three reinforcement scenarios. Number of subjects in parenthesis.

289 An optimal Bayesian learning model predicts response times

290 Our reversal-learning task contains contingencies that create expected and unexpected uncertainties
291 (Pulcu and Browning, 2019). Expected uncertainty emerges with probabilistic reinforcement (random
292 but balanced reinforcement), whereas unexpected uncertainty arises from the experimental design's
293 implied volatility (when the reinforcement conditions change between blocks; **Figure 2D**). We
294 implemented a Bayesian Learning (BL) algorithm (see **Methods**) to estimate the sources of uncertainty
295 in our task. This ideal observer model takes the reward rate from previous observations and transforms
296 the agent's belief about the task's state by updating representations of reward and volatility through
297 multivariate probability distributions (Behrens et al., 2007; Trevino et al., 2021). Therefore, to quantify
298 individual differences in the feedback experience when solving the reversal-learning task, we fitted the
299 BL to the choice data from each participant. The algorithm calculated and returned the reward (r) and
300 volatility (v) estimates as a function of the experimental trials (group averaged responses illustrated in
301 **Figure 3A**). The hierarchical aspect of the model has been discussed before (Trevino et al., 2021).

302 We next averaged the BL estimations from the four training blocks per participant (experimental
303 time-line in the lower panel of **Figure 3A**). The averaged r estimation rates (black) were similar for left
304 and right reinforcement (left | $84.65\% \pm 1.01\%$; right | $83.89\% \pm 0.93\%$; $n = 111$), but were ~40%
305 smaller with alternating reinforcement (alternation | $49.28\% \pm 0.38\%$; non-parametric Kruskal-Wallis
306 test with Bonferroni correction, $P < 0.001$; **Figure 3B**). Faster changes in r estimations reflect a greater
307 influence of recently experienced events (Pulcu and Browning, 2019). Likewise, v (kelly green) were, on
308 average, similar for left and right reinforcements (left | 0.17 ± 0.002 ; right | 0.17 ± 0.001 ; $n = 111$), but
309 they were ~30% higher with random reinforcements (alternation | 0.22 ± 0.002 ; $P < 0.001$; **Figure 3B**).
310 **Figure 2H,I**, and **Figure 3B** illustrate how the participants exhibited a wide range of choice variability,

311 r , and v estimates, particularly when solving our task's uncertain components (see also (Pulcu and
312 Browning, 2019)).

313 We wondered whether r and v estimates were sensitive to attentional factors. We reasoned that
314 these values should differ between trials that led to correct and incorrect choices (Trevino et al., 2016).
315 We extracted the response times (RTs) from correct and incorrect choices (**Figure 3C**), and employed
316 linear regression models (using “fitlm” function from MATLAB; modelspec: “linear”) to test whether
317 these RTs exhibited a dependency to r (**Figure 3D**) and v estimates (**Figure 3E**). Interestingly, when
318 reinforcing same-side choices, lower RTs were associated with higher r values for correct but not
319 incorrect trials. RTs also increased with v estimates for correct but not for incorrect choices. This result
320 shows how the sensitivity of the RTs to r and v could be used as an indirect measure of confidence by
321 the participants, where lower v estimates are associated with faster responses (Zylberberg et al., 2016).

Figure 3 | Reward and volatility estimations through a Bayesian Learning model. (A) Calculated reward (r) and volatility (v) estimations using an optimal Bayesian learning algorithm (see **Methods**; Behrens et al., 2007). **(B)** Averaged r and v associated with the reinforcement conditions from the

326 reversal-learning task. (C) Group average response times (RT, in s) for correct (blue) and incorrect (red)
327 choices. Inset shows the experimental time-line. Panels on the right side show scatter plots of RTs as a
328 function of r (D) and v (E). Number of subjects in parenthesis.
329

330 **Bayesian learning estimations contain information about the PTs**

331 Median splits constitute a useful and legitimate approach for examining relationships between factors
332 and dependent variables (Iacobucci et al., 2015). The method consists of forming two subgroups
333 depending on whether the PT scores were greater or smaller than the group median before performing
334 further analyses (Trevino, 2014; Trevino et al., 2016). Therefore, we divided the PT scores into strong
335 and weak groups (median split) to analyze whether the BL estimates contained trait information. In
336 agreement, we found that estimates for schizotypy (trait #1), somatoform (trait #2), anxiety state (trait
337 #3), and anxiety trait (trait #4) unveiled Bayesian computation differences (asterisks depict a $P \leq 0.05$,
338 with a Kolmogorov-Smirnov test, **Figure 4**). In many of these cases, the r and v estimation curves from
339 ‘strong’ and ‘weak’ groups remained well-separated throughout the training block. This outcome
340 implies that some of the PTs may be correlated with unique learning processes, as understood from an
341 optimal Bayesian learning perspective. Therefore, such learning differences should be useful to
342 understand PTs (Murphy and Msetfi, 2014).

Figure 4 | Relationship between Bayesian learning estimates and some psychological traits. Panels show Bayesian reward (r ; superior learners: continuous black line, inferior learners: dotted red line) and volatility (v ; superior learners: continuous kelly green line, inferior learners: dotted navy blue line) estimates from participants forming ‘higher’ and ‘lower’ performers. This was achieved using a median split of the participant’s r and v estimates and tracking their corresponding PTs (asterisks depict a $P \leq 0.05$, using a Kolmogorov-Smirnov test). Number of subjects in parenthesis.

353 **Behavioral profile quantified with the reversal-learning task predicts PTs**

354 The reversal-learning task helped us to characterize a learning ‘fingerprint’ from each participant
355 (Trevino et al., 2021). To further explore the link between the behavioral factors from the reversal-
356 learning task (*i.e.*, the predictors) and the PTs (*i.e.*, the response variables), we employed a multivariable
357 linear regression model (MLRM; **Figure 5A**). We collected a total of 24 behavioral metrics extracted
358 from the reversal-learning task (*i.e.*, a multimetric behavioral profile), including the stationary and
359 transition entropies (Trevino et al., 2021). Using correlation analysis, we found that many of the
360 predictors and response variables were not entirely independent from each other (**Figure 5B**). This
361 suggests that the behavioral profile could be condensed into a more compact and powerful version.

Figure 5 | Multivariate linear regression model. (A) Tables illustrate the seven response variables (*i.e.*, the PTs, enclosed in a dotted rectangle) and the 24 predictors extracted from the reversal-learning task (tea green background). We combined predictors with the PTs and applied a multivariable linear regression model (MLRM) to extract empirical slopes (Trevino et al., 2021). (B) The high cross-correlation coefficients across pairs of predictors (left panel) and response variables (right panel) reveal that many of these parameters are not fully independent from each other.

We then conducted the MLRM analyses and plotted the regression coefficients' strength as colored squares as a function of each block's training trial. We established the coefficients' empirical significance by comparing their values against 1000 regressions obtained with randomly permuted predictors (see **Methods**). We took $P \leq 0.05$ as a threshold and plotted non-significant (n.s.) coefficients as empty (*i.e.*, white) rectangles (**Figure 6A**). All these panels confirm that behavioral features extracted from the reversal-learning task contained information about the PTs' strength. To assess and visualize the differences across PT regressors, we plotted the three main principal components (PC) of the regression coefficients in a Cartesian coordinate system (each PT is represented with a point, error bars are standard deviations; **Figure 6B**). In addition, to assess the similarity across regression coefficients, we calculated the Euclidean distances (from the three PCs) across pairs of PTs (**Figure 6C**). Small distances imply overall similar MLRM regression coefficients, difficulting discrimination of PTs. In contrast, large distances imply a good discriminability of PTs by using the behavioral attributes from the reversal-learning task. **Figures 6B and 6C** revealed that anxiety state stand out from the rest, with more similar behavioral configurations for the remainder of the PTs. The MLRM analysis reveals that a multimetric behavioral profile can be used to classify and complement large self-reported personality questionnaires.

Figure 6 | Interdependence between behavioral attributes from the reversal-learning task and psychological traits. (A) Regression slopes for the MLRM as a function of the trials within each block. Empty rectangles represent non-significant (n.s.) slopes (see **Methods**). (B) Implementation of principal component analysis (PCA) for dimensionality reduction of our 24 regression coefficients into three main dimensions. Fraction of explained variance: PC1: 71.46% $\pm$ 5.13%, PC2: 12.55% $\pm$ 2.27%, PC3: 5.85% $\pm$ 1.44%. (C) Euclidean distances across pairs of PTs. Bigger distances imply stronger differences between regression coefficients. (D) Cumulative match curves calculated using different sets of

396 predictors, with their strength identified by using a step-wise regression learner (Trevino et al., 2021).
397 Stronger predictors render more accurate classification. Number of subjects in parenthesis.
398

399 **Behavioral attributes from the reversal-learning task as an individuality measure**

400 Because the MLRM analyses revealed a strong relationship between predictors from the reversal-
401 learning task and the PTs, we next explored the possibility of using the information in such behavioral
402 features to identify the participants. We implemented a simple linear classifier that minimized the
403 difference between partial and final predictors, as described before (Trevino et al., 2020;Trevino et al.,
404 2021). We rated their predictive power on the response variables (*i.e.*, the PTs) using a step-wise
405 regression learning procedure (Matlab Regression Learner App; (Trevino et al., 2021). The predictors
406 sorted in order of importance were: 1, 16, 5, 10, 17, 12, 7, 11, 6, 13, 18, 14, 2, 19, 3, 4, 20, 22, 23, 15, 9,
407 21, 24, 8 (these numeric IDs correspond to predictors displayed in **Figure 5A**). Notably, the best
408 predictor for all PTs was $|m|$ (rectified slope), which constitutes a raw, yet powerful metric of the
409 learning rate. We created the cumulative characteristic curves by using increasing epoch durations. As
410 anticipated, we found that prediction accuracy increased with epoch duration (against classifications
411 made with 1000 random permutations of the predictors; rnd in caramel-brown). Also, prediction
412 accuracy improved faster when using stronger predictors (tangerine and carmine reds; predictors
413 contained within percentiles 75%-100%: 1, 16, 5, 10, 17, 12; **Figure 6D**). This result indicates that
414 multimetric behavioral predictors exhibited different predictive power to identify the participants.

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417 **Discussion**

418 Using a multiple-baseline reversal-learning task, we characterized how individuals adopted various
419 strategies linked to different error checking levels and heterogeneous learning curves. These learning
420 curves and other behavioral parameters were specific for each individual (Byrom and Murphy,
421 2018;Trevino et al., 2021). Such individual differences in human associative learning substantially
422 impact adaptive strategies in rapidly changing environments. Some disruptions in such adaptive
423 behaviors have been associated with some cognitive aspects of psychopathology (Corlett et al., 2009).
424 Human learning flexibility can be integrated into a general framework in which model parameters
425 represent and lead to variance in learning (Rescorla and Wagner, 1972;Trevino et al., 2011;Byrom,
426 2013;Glautier, 2013;Trevino, 2015;2020).

427 It has been shown that different amounts of uncertainty influence how decision-makers use
428 previous events to guide their choices. Expected uncertainty reduces the amount of information that
429 individual trials provide (*i.e.*, an optimal strategy is to rely on a wider choice-history window). In
430 contrast, unexpected uncertainty involves a radical change in reinforcement conditions that require quick
431 adaptation (*i.e.*, the optimal strategy is to rely on a short choice-history window; (Pulcu and Browning,
432 2019). Trial and error learning algorithms provide powerful explanations of how humans can learn to
433 choose actions that result in more rewards and fewer punishments. Similarly, Bayesian learning models
434 (BL) assess how individuals learn about environments with expected and unexpected changes in
435 probabilistic relationships (Lawson et al., 2017). We employed an optimal BL to estimate how
436 participants adapted to changes in expected and unexpected sources of uncertainty (Pulcu and Browning,
437 2019). The BL algorithm allowed us to characterize each participant's reward (r) and volatility (v)
438 estimates while learning about the reversal-learning task. We explored the possibility of an attentional
439 component regulating the r and v estimations and found that the response times (RTs) depended on r and

440 v estimations for correct but not incorrect choices. These RT differences represent an indirect measure of
441 confidence in the task (Zylberberg et al., 2016). It remains an open question how the RT distributions
442 relate to the BL and confidence estimations (Whelan, 2008; Trevino et al., 2016; Trevino, 2020).

443 We characterized the psychological traits (PTs) of the participants using the HiTOP scale (Kotov
444 et al., 2017). Although there are other relevant classification systems (Costa and McCrae, 1992; Gillan et
445 al., 2016), we chose PTs based on specters from the HiTOP due to the recent and intense research
446 behind it. Interestingly, although it's clear that PTs influence learning in humans (Msetfi et al., 2017),
447 these effects are not generally integrated into associative learning models (Rescorla and Wagner,
448 1972; Le Pelley, 2004; Esber and Haselgrove, 2011). Our results revealed r and v estimation differences
449 in anxious and schizotypal individuals solving the reversal-learning task were probably due to an
450 impaired reconfiguration between expected and unexpected uncertainty strategies (Corlett et al., 2009).
451 Moreover, our results showed that behavioral parameters extracted from the reversal-learning task
452 contained PT information and confirmed the idea that anxious individuals perform worst in volatile
453 environments (Browning et al., 2015). Our approach involved using a robust multimetric behavioral
454 characterization to describe the learning curves and their relationship with the psychometric scales. The
455 analysis revealed that some PTs (*e.g.*, somatoform, anxiety trait, impulsivity) had similar behavioral
456 manifestations and maybe even a common internal variation source impacting such behavioral outputs.
457 In contrast, anxiety state was the PT associated with the most distinguishable behavioral profile.

458 Beyond the well-known disruptions in latent inhibition and blocking, previous works have
459 shown how schizophrenia patients and with schizotypy exhibit impaired stimulus salience (Haselgrove
460 and Evans, 2010; Byrom, 2013) and context (Uhlhaas and Silverstein, 2005) processing capacities.
461 Misestimating the sources of uncertainty leads to sub-optimal behavior. It could reflect a failure to detect
462 the state of complex environments or to choose the correct course of action. Difficulties in estimating

463 uncertainty could be one mechanism linked to disorders like depression, anxiety, and neuroticism, which
464 show learning difficulties (Pulcu and Browning, 2019). Obsessive-compulsive disorders (OCD) are also
465 driven by deficiencies in the way participants update their behavior and establish confidence about the
466 tasks being solved (Gillan et al., 2016;Seow and Gillan, 2020). Adults with autism spectrum disorder
467 (ASD) exhibit intolerance to change and tend to overestimate the sensory environment's volatility
468 (Lawson et al., 2017).

469 We found that schizotypy, somatoform, and anxiety states predicted some differences in the
470 behavioral attributes from the reversal-learning task. These results raise the possibility of using learning
471 estimates (e.g., v) to detect differences in this population. Moreover, reversal-learning tasks have been
472 used to investigate PTs given their sensitive properties to identify individual differences (Budhani et al.,
473 2006;Gillan et al., 2016;Dargis et al., 2017). Using a multivariable linear regression model, we showed
474 how behavioral differences on the reversal-learning task contained information about the PTs from the
475 HiTOP specters. The strongest predictor was tightly linked to a raw metric of the learning rate. We also
476 found that behavioral parameters extracted from the reversal-learning task acted as sensitive trait
477 variables that individuals exhibited while solving the task (*i.e.*, cross-situationally consistent behavior;
478 (Allport, 1961;Harris et al., 2016). It would be crucial to confirm that these behavioral metrics are
479 consistent across situations (Trevino et al., 2021) and whether they are enduring, namely, if they hold
480 test-retest reliability in intervals ranging from days to weeks even to years (Harris et al., 2016).

481 Previous work suggests that some personality traits are linked to elevated levels of delay
482 discounting (reduction in the present value of a delayed outcome), such as some psychiatric conditions,
483 personality/ disorders, pathological gambling, drug abuse, among others (Odum, 2011). Impulsivity can
484 also be characterized as a desire for rapid over long-term rewards (increased delayed discounting of
485 rewards) and decreased cognitive capability (Bobova et al., 2009). Internal and external causes interact,

486 conforming a complicated and integrated network of interactions that could explain the learning
487 differences between individuals in a population (Sauce and Matzel, 2013).

488 One of the main limitations of our work is that we assumed that participants behaved as optimal
489 Bayesian learners. However, it is still under debate which model offers the best description of how
490 humans estimate uncertainty (Pulcu and Browning, 2019). Correlational approaches and regressions
491 help explore the influence of certain variables on behavioral output across individuals. Still, these
492 approaches have limited capacity to understand behavior. A general mechanism or a theoretical
493 framework is crucial to understand these relationships (Byrom and Murphy, 2018). Indeed, more
494 research is needed to explore and isolate which factors underlie individual behavioral differences.

495 In synthesis, we presented an exploratory study that related behavioral responses to a reversal-
496 learning task with seven PT specters from the HiTOP scale. We implemented a robust behavioral
497 characterization to construct multimetric behavioral profiles of the participants. We found that such
498 behavioral profiles served as a behavioral signature from the participants and predicted the PTs.

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Conflict of Interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be considered a potential conflict of interest.

Author Contributions

Conceptualization: MT and SC; Methodology: MT and SC; Resources: MT; Supervision: MT, BV, and PO; Investigation: MT, SC, BV, PO, and RM; Visualization: MT and RM; Writing – original draft: MT; Writing – review & editing: MT and SC; Funding Acquisition: MT.

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